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Digital Images Retrieval Using Iterative Technique

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Abstract—*Use of efficient image restoration method gains most interest due to its close relation to the improvements happen in the fields of compression and communications. Image restoration tries to improve the quality of degraded image by undoing the blurring and reducing the noising using the de-convolution technique for producing an estimate image is approaches the original one. The adopted image retrieval technique uses the Meads filter that working in the frequency domain for achieving the recovered image. In order to test the performance of the adopted method, a gray image is used in the implemented test with a pixel resolution of 8bit.The practical work includes two phases: degradation phase and retrieval phase. The degradation contains two stages within, they are: the blurring and noising. While the retrieval phase depends on processing the amount of blurring that defined by the blurring parameter (σ), and then rejecting an amount of the noise that determined by the noise parameter (SNR). Different values of blurring and noising parameters are estimated when applying the Mead's technique for achieving the retrieved image. Results showed high matching between the retrieved image and the original one. Quality measures prove the retrieved image converge the original image with little differences in between, where the amount of similarity score is 92%.*

Keywords— *Image restoration, Mead's filter, blurring, noising, degraded image*.

I. Introduction

The field of image restoration, image de-blurring or image de-convolution concerns with an estimation of the uncorrupted image from degraded one. The restoration of the image classified into the degradation phase and the restoration phase [1].The degradation phase is concerned with the real image that degraded by the blurring and the extra noise. The resultant image of this part called the degraded image. Whereas, the restoration phase is concerned with using many filters up on degraded image and estimating a picture for the original image to be produced as an output. Whereas, the image restoration methods divided into two classes blind and non-blind [2] [3].Blind restoration is the method which the blurring factor is unknown. Primary knowledge of h(x,y) not needed but the blurring factor estimation necessary to use to de-blur the image. The non-blind restoration is the method which the blurring factor is known a prior knowledge of h(x,y) needed. Remove the blurs from the degraded images be conditioned on the blurring function knowledge. The degradation model results from the blurring function and the effect of noise function. The model of degradation process in spatial domain is given by the following formula [4]:

$$g(x,y) = h(x,y) \circledast f(x,y) + n(x,y) \quad (1)$$

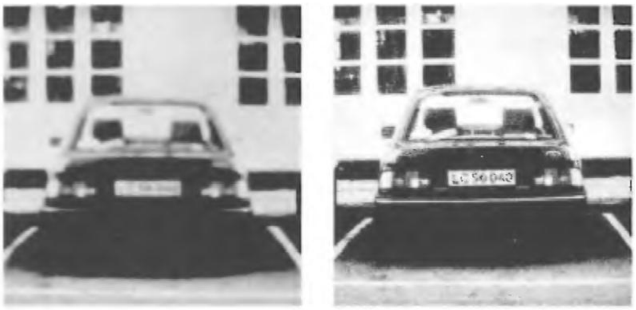
Where g(x,y) represent the degraded image, f(x,y) represent the original image, n(x, y)represent the additive noise function and h(x,y) represent the blaring function (degradation function). The real image and the noise combined linearly, so that the problem of restoring the real image from the distorted image is defined as a linear image retrieval problem.

Recently, the field of image retrieval has seen a tremendous growth in interest; many articles are published to overview excellent results in the field of interest. In [5], an iterative Wiener filter was adapted to retrieve degraded images. The adapted filter was designed for restoring astronomical images that are blurred with space-invariant point spread function and corrupted with additive noise .The result using an adaptive filter were compared quantitatively, using mean square error (MSE). This method showed better performance for restoring the degraded images, especially for high signal to noise ratio. Also, an iterative algorithm based on Constrained Least Squares Regularization Algorithm was proposed to restore the image in [6]. Three restoration algorithms namely, Local Polynomial Approximation Intersection of Confidence Interval rule and Sparse Prior De-convolution Algorithm and Richardson-Lucy De-convolution Algorithm are applied on different types of degraded image to indicates the best restoration performance among the three used methods as documented in [7]. In [8], an iterative image restoration technique was proposed using Wiener filter to restore the degraded face images, which improved the recognition performance and the quality of the images. In [9], an adaption to iterative gradient descent algorithms is proposed to be applied on Barzilai-Borwein Algorithm and the Conjugate Gradient Algorithm for images retrieval. Then, [10] studied and analyzed the comparison between various image restoration techniques. In [11], an improvement on the quality of the degraded images by using an iterative linear restoration Tikhonov-Miller regularized restoration filter is documented. The prior information about the degradation phenomena help to implement the blind mode of the restoration filter. Results obtained by Tikhonov-Miller filter were compared with that given by non-iterative Wiener filter using the root mean square error (RMSE).

In the present paper, the used technique of image retrieval is non-blind, in which the blurring function is known and the space is invariant. This retrieve technique aims to reconstruct the original image (estimated object) from degraded version using adaptive Mead's algorithm, Mead's algorithm is one of the type non- blind, linear, constrained, iterative retrieval technique.

II. Image Retrieval

Image Retrieval is the operation of estimating the clean original image from a corrupt one. Corruption may come in many forms such as motion blur, noise and camera defocusing. Image retrieval is performed by reversing the process that blurred the image and such is performed by imaging a point source and use the point source image, which is called the Point Spread Function (PSF) to restore the image information lost to the blurring process, Figure 1 shows degraded image and its retrieved image by the Mead's filter. Mead's filter is one of the most interesting filter is used for image retrieval.



(a) Degraded image. (b) Retrieved image.
Fig. 1. Image retrieval by Mead's filter.

The iterative Mead's filter is related to the least square method, it obtained the result of restoration iteratively non in one shot solution, the Mead's filter adaptive to constrained least square method that find the optimal estimate for $\hat{f}$ of the un-known taeget function f and generally formulated as constrained optimization Problem of $min\|C\hat{f}\|^2$ that satisfying the following constrained condition:

$$\|g-H\hat{f}\|^2 < \epsilon^2 \quad (2)$$

where C is suitable weighting matrix, C could be a Laplacian operator or signal to noise ratio. The constrained problem can be transformed to unconstrained problem by using Lagrangian multiplier method so the estimate for $\hat{f}$ found by reduce error function with respect to $\hat{f}$ as given in the following relation:

$$E_1(\hat{f})=\|g-H\hat{f}\|^2+\alpha\|C\hat{f}\|^2 \quad (3)$$

The solution is usually found by $\frac{\partial E_1}{\partial \hat{f}}=0$ one shot solution since no iteration involved

$$\hat{f} \;=[H^\sim H+\alpha C^\sim C]^{-1}H^\sim g \quad (4)$$

where, α is regularizing parameter that controls the tradeoff between the amount of restoration and amount of noise. The solution of equation (4) found iteratively by

$$\hat{f}_{k+1}=\hat{f}_k+\beta[H^\sim g–(H^\sim H+\alpha C^\sim C)\hat{f}_k \quad (5)$$

Where β control the convergence of the iterations. The damped least square (DLS) restoration method represented as constrained optimization problem of $min_{\Delta\hat{f}}\Delta\hat{f}^\sim C\Delta\hat{f}$ that denoted as follows:

$$\|g-H\hat{f}\| < \epsilon \quad (6)$$

Where $\Delta\hat{f}$ is correction vector or optimization step and C diagonal weighting matrix. The DLS even represented as unconstrained problem of $min_{\Delta\hat{f}}\|g-H\|+\alpha^2\Delta\hat{f}^\sim C\Delta\hat{f}$, where α is regularizing parameter. The restoration problem solved iteratively by Mead's recurrence method by equation

$$\hat{f}_{k+1}=\hat{f}_k+[H^\sim H+\alpha C]^{-1}H^\sim(g-H^\sim\hat{f}_k) \quad (7)$$

$$\hat{f}_{k+1}=\hat{f}_k+w(g-H^\sim\hat{f}_k) \quad (8)$$

where

$$w=[H^\sim H+\alpha C]^{-1}H^\sim \quad (9)$$

III. PROPOSED RETRIEVAL METHOD

The concept of multistage processing and quality measurement has been used to design the proposed image restoration method. It is claimed that these stages can beneficially be combined to establish a fast and efficient retrieval technique. The proposed image retrieval method is composed of two phases, they are: degradation and restoration. The degradation is an image preparation phase, which is responsible on impact the quality of test image by the degradation process that includes blurring and noising the test image. Whereas the restoration is a post processing phase that responsible on restore the quality of the image by using the filtering technique, which is carried out once by the spatial domain and another by the frequency domain In the degradation phase, the degraded image is established by blurring and noising the test image. The blurred image is made once in the spatial domain and another in the frequency domain. The blurred image in the spatial domain is made by convolving the test image with a blurring function that separated along the image according to Gaussian distribution. While, the blurred image that made by frequency domain is resulting from inversely transforming the result of multiplying the transformed test image by the transformed same blurring function that behaves as Gaussian. Whereas, the addition of the noise to the blurred one to make the degraded image is also carried in the spatial domain by convolving a specific amount of noise that separated according to Gaussian distribution, which is carried out in the frequency domain by multiplying the transformed blurred image with the transformed Gaussian function. The restoration is also performed by applying the mead's filter once in the spatial domain by the convolution with circulant matrix, and another in the frequency domain by reconstructing the degraded image in the high frequency band. Algorithms (1 and 2) present the programming procedures of proposed image retrieval in both spatial and frequency domains.

Algorithm 1. Image retrieval in the spatial domain.

Input: *f* \\ 2D array of represent one color component of original image of (*w*,*h*) dimensions. σ\\ fractional number represents the width of blurring function (σ= 1,2,3) *SNR*\\ fractional number represents the signal to noise ratio (SNR=5,10,20,30)
Output: *d* \\ 2D array represents the retrieved image.
Procedure: **Step1:** *Generate blurring function g_F of variance σ^2 and zero mean.* ***Loop for each pixel (x,y)***:g_F(*x*,*y*)=(1/Sqrt(2×*Pi*×σ))*(***Exp***(-(*x* ^ 2 +*y* ^ 2)/(2×σ^ 2))

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Step2: *Image blurring by convolving f with* g_F.

Set g_F as Gaussian Function of determined σ.

Loop For each pixel (x,y): *b*(x,y)⟵*b*(x,y)+ *f*(x,y) ×g_F(w-x,h-y)

Step3: *Generate Normal noising function* g_S *of SNR variance.*

Step4: *Image noising by adding picked probability from* g_S *into blurred image b(x,y).*

Set pick probability⟵Random number from Gaussian distribution of index *k*

Loop For each pixel (x,y): *d*(x,y)⟵*b*(x,y)+*k*

Step5: *Create the circulent matrix C*

bs(x,y)←Shift *b*(x,y) by one element to the right and replace the first element with the last element overflowed from shifting

bsT(x,y)←Transpose *bs*(x,y) by flipping the bottom and top elements on the main diagonal

C(x,y) ← *bsT*(x,y) / (*bsT*(x,y) * bs + (1 / SNR ^ 2))

Step6: *Restore the degraded image using the circulent matrix C*

Set *r*(x,y)←*d*(x,y)

Loop For each pixel (x,y): *r*(x,y)←*r*(x,y)+*C*(x,y)×(*d*(x,y) –*bs*(x,y)×*r*(x,y)

End.

Algorithm 2. Image retrieval in the frequency domain.

Input:

f \\ 2D array of represent one color component of original image.

σ\\ fractional number represents the width of blurring function (σ= 1,2,3)

SNR\\ fractional number represents the signal to noise ratio (SNR=5,10,20,30)

Output:

r \\ 2D array represents the retrieved image.

Procedure:

Step1: *Generate blurring function* g_F *of variance* σ^2 *and zero mean.*

Loop for each pixel (x,y):g_F(x,y)=(1/Sqrt(2×*Pi*×σ))*(***Exp***(-(*x* ^ 2 +*y* ^ 2)/(2×σ^ 2)))

Step2: *Image blurring by Fourier transform.*

Set MFT = FFT[*f*] ×FFT[g_F] *// FFT is the Fourier Transform*

Set *b*(x,y)=IFFT[MFT] *// IFFT is the Inverse Fourier Transform*

Step3: *Generate Normal noising function* g_S *of SNR variance.*

Step4: *Image noising by adding picked probability from* g_S *into blurred image b(x,y).*

Set pick probability⟵Random number from Gaussian distribution of index *k*

Loop For each pixel (x,y): *d*(x,y)⟵*b*(x,y)+*k*

Step5:

Set *D(x,y)=FFT*[*d(x,y)*]

Set *R* as the results of apply *Cf* on the transformed image *D*.

Set *r*(x,y) ← IFFT[*R*(x,y)]

End.

IV. RESULTS AND DISCUSSION

There are detailed explanations related to the results achieved through implementing each stage in the proposed retrieval method. The results are presented in figures and tables including the final indication about the retrieval performance. Then, quantitative and qualitative analysis is estimated to evaluate the performance of the proposed retrieval method. The blurring function is generated at different values of σ, the test shows that the useful values are: σ=1, 2, and 3. Figure 2 presents the generated Gaussian function, which is the PSF at the different considered values of σ. The increase of blurring due to higher σ leads to increase the blurring of the resulted image.

Figure 3 presents the probability density function (PDF) of the generated Gaussian noise function at the different considered values of *SNR* with zero mean, *SNR*=30, 20, and 10, which represents the amount of appearing same value in the randomly obtained generated noise distribution. It is shown that the increases of the value of σ leads to increase the width of the blurring function that affects the behaviors of the power and modulus for each case of blurring function.

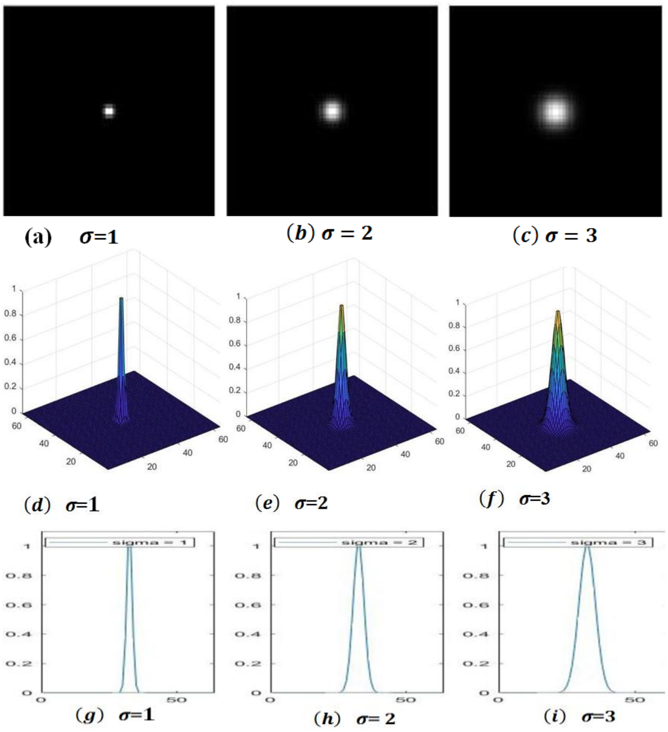

Fig. 2. Behavior of blurring function for different σ values.

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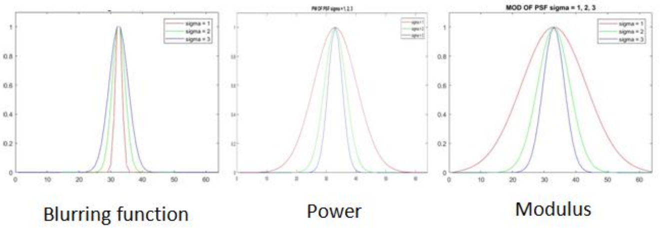


Fig. 3. Plots of blurring function, power, and modulus for different values of σ.

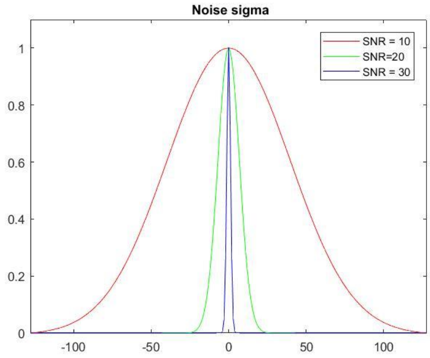
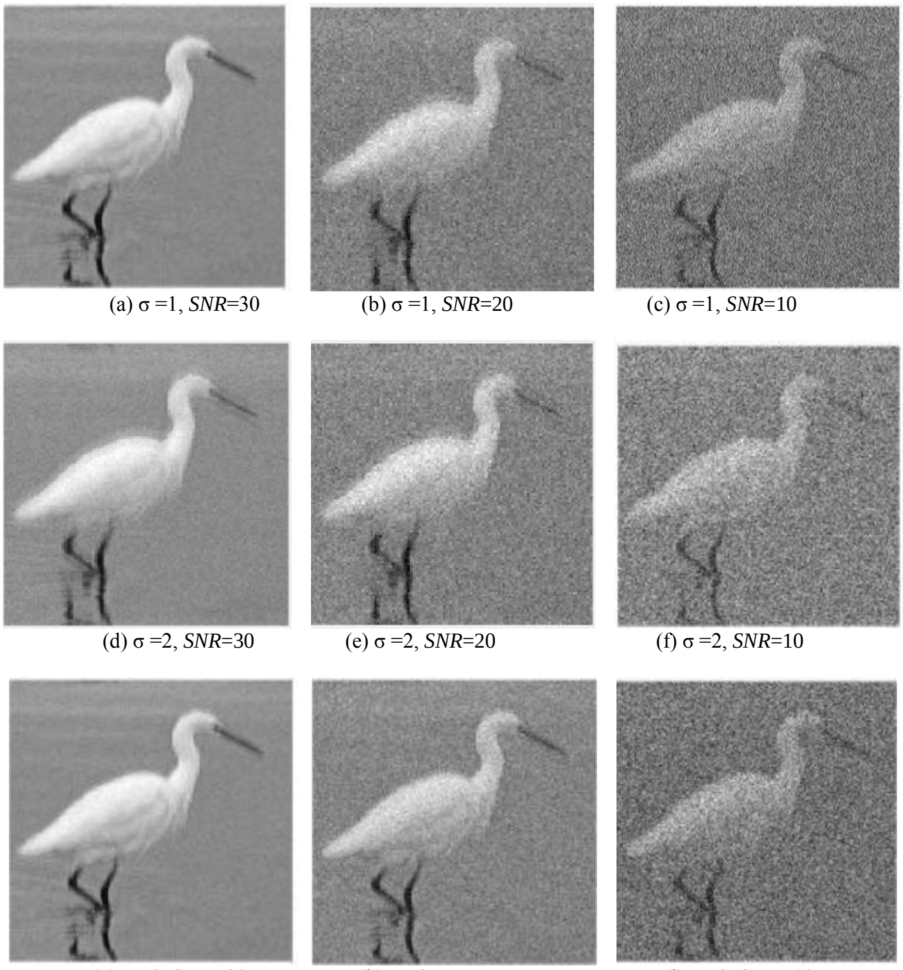


Fig. 4. PDF behavior of gaussian noise with defferent values of *SNR*.

In the degradation phase, the results of image degradation in the spatial domain processing that produced by convolving the additive Gaussian noise function with the blurred image. The three blurring cases of σ =1, 2and 3 are considered, where the *SNR* is considered to be 30, 20, and 10 in each case. As a result, there are nine degraded images are resulted from combining both values of σ and *SNR* as Figures 5 shows. It is noticeable that the increase of blurring due to higher *σ* leads to increase the blurring of the resulted image, the edges of the blurred images in cases (g, h, and i) of the figure are appeared less sharpening than that shown in cases (a, b, and c) in same figure. Also, it is shown that the increase of the *SNR* value leads to increase the width of the PDF function, which indicates the rising behavior of the noise comparable with the original image. The PDF of *SNR*=10 is narrow in comparison with the behaviors of *SNR*=20 and *SNR*=30, and also the width of *SNR*= 20 is less than that of *SNR*=30. Various values of SNR affect the density of the histogram, which in turn will affect the density of the noise found in the resulted degraded image. In addition, the increase of noising due to higher *SNR* leads to increase the noise of the resulted image, the extended regions of the noisy images in cases (a, d, and g) are appeared sinuous in comparison with that shown in cases (c, f, and i).



(a) σ =1, *SNR*=30 (b) σ =1, *SNR*=20 (c) σ =1, *SNR*=10

(d) σ =2, *SNR*=30 (e) σ =2, *SNR*=20 (f) σ =2, *SNR*=10

(g) σ =3, SNR=30 (h) σ =3, SNR=20 (i) σ =3, SNR=10

Fig. 5. Resulted degraded Bird image for different values of σ, and SNR.

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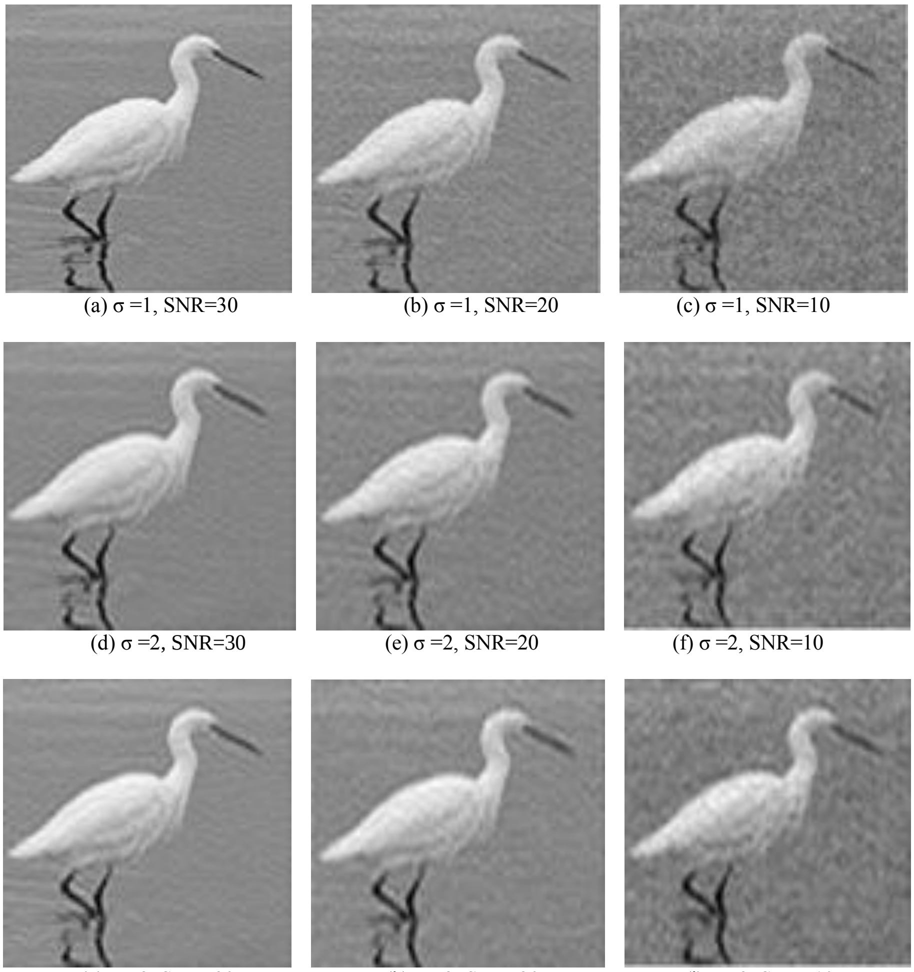


(a) σ =1, SNR=30 (b) σ =1, SNR=20 (c) σ =1, SNR=10

(d) σ =2, SNR=30 (e) σ =2, SNR=20 (f) σ =2, SNR=10

(g) σ =3, SNR=30 (h) σ =3, SNR=20 (i) σ =3, SNR=10

Fig. 6. Resulted restored image for different values of σ, and SNR, in which the iteration number is 20.

In the restoration phase, the iterative Meads filter is used in the spatial domain. The restoration iteration is determined either by reaching the maximum number of iteration (*I*=20), or when there is no change may detected between the current resulted image and the next one. Figure 6 shows the results of the image retrieval using Mead's filter. The increases of the iteration numbers are reasonably leads to eliminate the effect of the noise not the blurring, more filtration leads to result smooth image with little noise. The smoothing impact the sharpness of the edges found in the image beside the extended spectrally homogenous region. It is noticeable that the restoration results are qualitatively appearing closer to the original image with decreasing σ and increasing *SNR*, best result is when σ=1 and *SNR*=30. Also, it is found that the number of iteration affects the restoration results, more accurate results are obtained at more iteration number. It is shown that the quality of the restored image is increased with less value of σ and greater value of *SNR*, this interprets that the best restored image is yield when σ =1 and *SNR*=30. The least σ refers to less smoothing occur in the image and less embedded cues are happen, in which the edges appear with small amount of smoothing is proportional to the breadth of the effected blurring function. Also, the greater value of SNR that shows better quality of restored image is due to the increase of the useful signal comparing with the assumed noise, where the useful signal is the information of the image cues.so that best restoration case is presented in figure 5 which restored distorted image by blurring function with sigma =1 and SNR =30.

In figure 6 presenting the result of Mead's method in 20 iteration for different regularization parameters for blurring with sigma= 1,2, and 3 and noise power is estimated from SNR =10, 20 and 30.

Figure 7 shows the original image, degraded image in which the estimated values of both σ and *SNR* are set to be 2 and 20 successively, and different cases of resulted restored images when the number of iterations of restoring the degraded image is varying as I=1, 5, 10, and 20. The mean square error (MSE) between each resulted case and the original image is computed, which is indicates the amount of divergence the resulted restored image into the original one due to the restoration process. Also, MSE indicates the amount of raising the quality of the restored image due to the restoration process. It is shown that the quality of the restored image increases with increasing the number of iterations. In such case, some amounts of the blur and noise are eliminated and the image is reformed time by time. Therefore, the best quality image is that resulted when the number of the iteration is considered to be maximum value. Actually, the effective performance of the used Meads filter make the image is fast reformed to be in acceptable form when the iteration number is 20. More iteration does not offer noticeable improvements in the restored image.

(a) Original (b) Deg MSE=792 (c) I=1, MSE=92.54

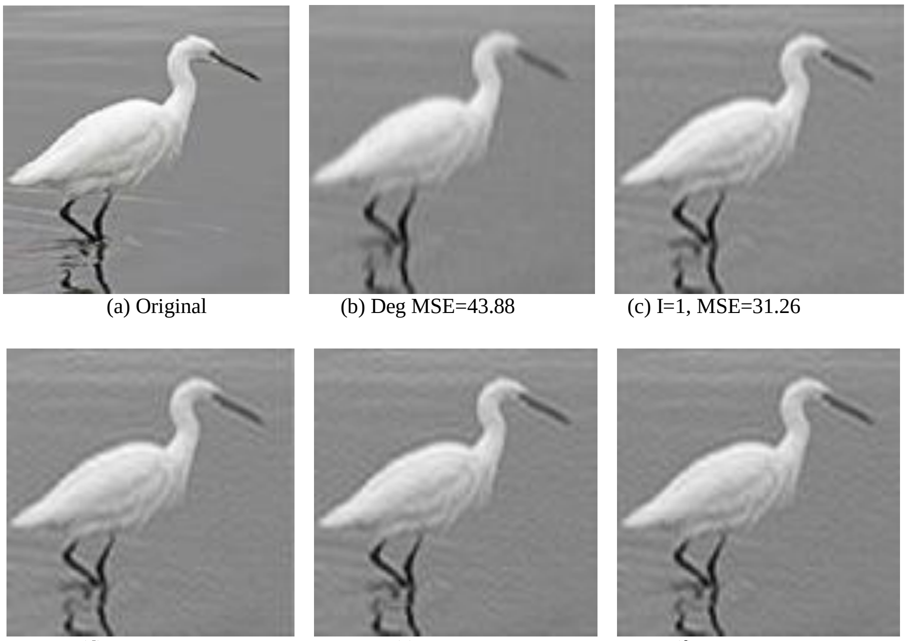
(d) I=10, MSE=80.56 (e) I=15, MSE=76.77 (f) I=20, MSE=77.5

Fig. 7. Resulted restored Bird image for σe=2 for different values of number of iterations applied on degraded image of σ=2 and SNR=10.

(a) Original (b) Deg MSE=112 (c) I=1, MSE=43

(d) I=10, MSE=40 (e) I=15, MSE=39.6 (f) I=20, MSE=38

Fig. 8. Resulted restored Bird image for $\sigma_e=2$ for different values of number of iterations applied on degraded image of σ=2 and SNR=20.



(a) Original (b) Deg MSE=43.88 (c) I=1, MSE=31.26

(d) I=10, MSE=27.1 (e) I=15, MSE=26.5 (f) I=20, MSE=25

Fig. 9. Resulted restored Bird image for σ_e=2 for different values of number of iterations applied on degraded image of σ=2 and SNR=30.

V. Conclusion

Mead's retrieval technique had better performance for recovering image which degraded with less degradation parameters little width of blurring function and high signal to noise ratio.

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