Image Restoration Using Modified Iterative Tikhonov Miller algorithim

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Abstract - Digital image started to including in various fields like, physics science, computer science, engineering science, chemistry science, biology

science and medication science, to get from it some important information. Image restoration field, is one of digital image processing fields cure about image improving the degraded image. Image restoration algorithms trying to "undo" the blurring function and the noise from the degraded image. The research focusses on linear non-blind image restoration. The images has been used, blurred by Gaussian blurring function with different standards deviation values and degraded by additive Gaussian noise with different signal to noise level "SNR". Iterative Tikhonov-Miller filter have been used to restore the degraded images. By using Root mean square error measuring we measure the quality of restored image. we concluded that, better restore for less degradation parameters, with high SNR.

Index Terms - Gaussian blurring function, Gaussian noise function,, degraded image, criterion function, Iterative Tikhonov-Miller filter, standards deviation,

noise level

1INTRODUCTION

Concern in digital image process field started in 1920, at the point when digitized picture of world news

events were 1st send by submarine cable among New York and London. A number of digital image process applications; like physics, pictures of experiments in such space as high-energy plasmas and electron microscopy habitually improved by pc techniques. And in medication applications, as an example, physicians are power-assisted by pc procedures that enhance the distinction or code the intensity levels into color for easier interpretation of x-rays, like process of X rays-chest and supersonic scanning, another example, medical image also used for detection of tumors or different malady in patient [1]. Image restoration is mention as an rising the image quality that is degraded byblurring and noise [2]. The degradation model used in the research consists of two portion, the blurring function and the noise function. In the case of additive noise, the degradation model in spatial domain is given by [1]: g(x,y)=H(x,y)+f(x,y)+n(x,y)(1)

Where g(x,y) is degraded image, f(x,y) is original image, n(x,y) noise, H(x,y) is circulant matrix of blurring function.

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In general, most effect which distort the image as aberration, non-homogeneous media, motion between the object and camera [3]. Image Restoration kind are often divided into two kind: Blind restoration and Non-Blind restoration. Blind restoration, the one within which operation of blurred unknown factor, therefor we create an estimate of the blurring operator and so using that estimate we have to deblur the image. Non-Blind restoration is that the one within which the blurring operator is noted, then we will take away blur from the degraded image using the noted of blurring function [4]. Iterative Tikhonov-Miller filter and Wiener filter are constrained linear restoration techniques, to derive them, we should to found a criterion function by letting Q be a linear operator on f. Consider the least-squares restoration problem as one of minimizing functions of the form $\left\| Q \hat{f} \right\|^2$, subject to is additive constraint $\|g - H\hat{f}\|^2 = \|n\|^2$. This approach introduces considerable flexibility in the restoration process because it produces different solutions for different choices of Q [1]. The addition of an equality constraint in the minimization problem can be handled without difficulty by using the method of Lagrange multipliers. The procedure is to express the constraint in the form $\alpha(\|\mathbf{g} - \mathbf{H}\hat{\mathbf{f}}\|^2 - \|\mathbf{n}\|^2)$ and then append it to the function $\|Q\hat{f}\|^2$. In other words, we seek \hat{f} that minimizes the criterion function [1].

$$J(\hat{f}) = \|Q\hat{f}\|^{2} + \alpha(\|g - H\hat{f}\|^{2} = \|n\|^{2})$$
(2)

Where α is a constant called the Lagrange multiplier and Q linear operator.

By differentiating Eq.(2) with respect to \hat{f} and setting the result equal to the zero vector yields [1]:

$$\frac{\partial J(f)}{\partial \hat{f}} = 0 = 2\dot{Q} Q \hat{f} - 2\alpha \dot{H}(g - H\hat{f}) \qquad (3)$$

The solution is obtained by solving eq.(3) for \hat{f} ;that is [1]: $\hat{f}=(\hat{H}H + \gamma \hat{Q}Q)^{-1}\hat{H}g$ (4)

Where $(\mathbf{H} \mathbf{H} + \gamma \hat{\mathbf{Q}} \mathbf{Q})^{-1} \mathbf{H}$ is Wiener filter equation, fis restored image and $\gamma = \frac{1}{\alpha}$.

The optimal solution is given by eq.(2) with $Q \approx C$ and we use the method of the steepest descent to minimize the objective function J(\hat{f}) in (2) gives the following iterations [5]:

$$\begin{split} \hat{\mathbf{f}}_{k+1} &= \hat{\mathbf{f}}_k + \beta \mathbf{r}_k = \hat{\mathbf{f}}_k - \frac{1}{2}\beta \, \nabla_{\mathbf{f}} \mathbf{J} \left(\mathbf{f} \right) |_{\hat{\mathbf{f}}_k} \\ &= \hat{\mathbf{f}}_k - \beta \left((\mathbf{H}^T \mathbf{H} + \alpha \mathbf{C}^t \mathbf{C}) \hat{\mathbf{f}}_k - \mathbf{H}^t \mathbf{g} \right) \end{split} \tag{5}$$

Where k is number of iteration, \hat{f}_{k+1} is restored image after k+1 iterations, \hat{f}_k is restored image after k iterations, β is control the convergence of the iterations and C is Laplacian operator. Eq.(5) is called Iterative Tikhonov-Miller equation. The advantage iterative procedures that are no matrix inverses need to be implemented, and the additional deterministic constraints can be incorporated into the solution algorithms [5]. There is several iterative method used [6-9].

2 EXPERIMENTAL RESULTS

satellite image used are 256*256 pixels in size, convolved with blurring function with different standards deviation values " degraded by additive Gaussian noise with different signal to n "SNR" to produce degraded image, Then restored with different f as Iterative Tikhonov-Miller filter

Image Restoration Algorithm by using Matlab language

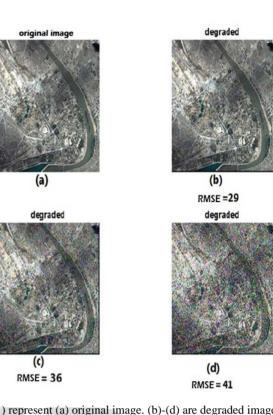
1- Read original image of size 256×256 type binary or RGB imag 2- Generating Gaussian function (size 256×256) with different a deviation.

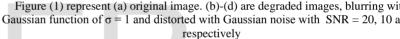
3-Generating random Gaussian noise with different noise level.

4- Convolve original image with Gaussian function to produce image.

5- Add Gaussian noise to blurred image to produce a degraded in 6- Estimate original image using different restoration filter such a filter, Tikhonov-Miller regularized restoration filter.

7- Calculate the Root mean square error (RMSE) from restore obtained by filters.





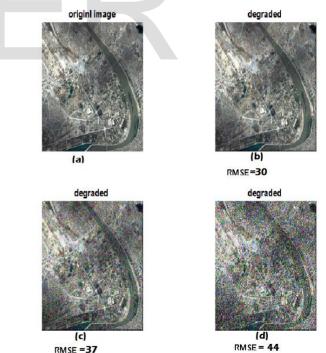


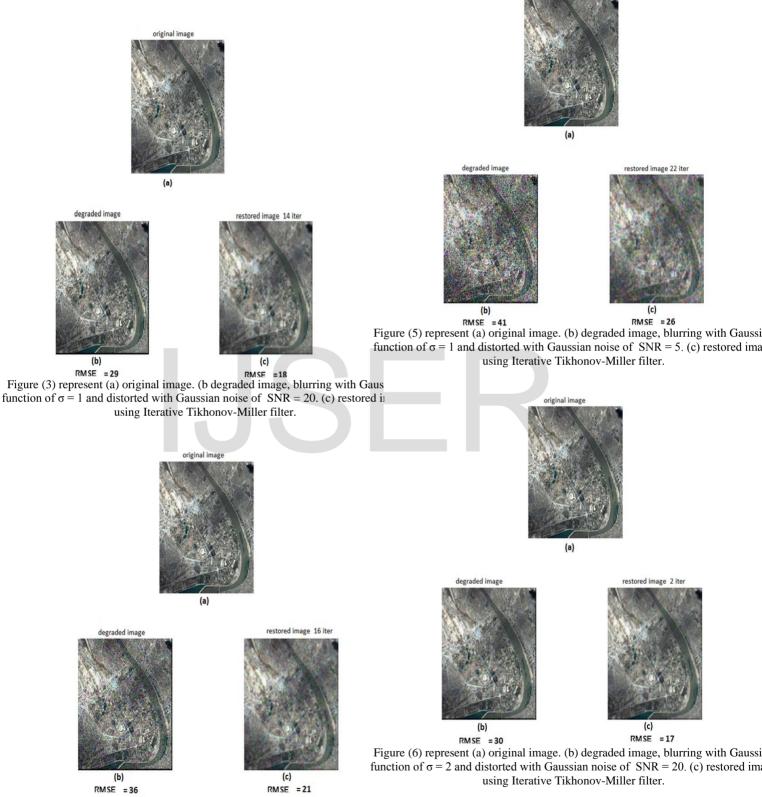
Figure (2) represent (a) original image. (b)-(d) are degraded images, blurring with Gaussian function of $\sigma = 2$ and distorted with Gaussian noise with SNR = 20, 10 a respectively

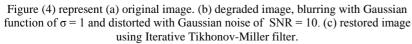
The degraded images will be restored with Iterative Tikhonov-Miller fil

1- Iterative Tikhonov-Miller filter

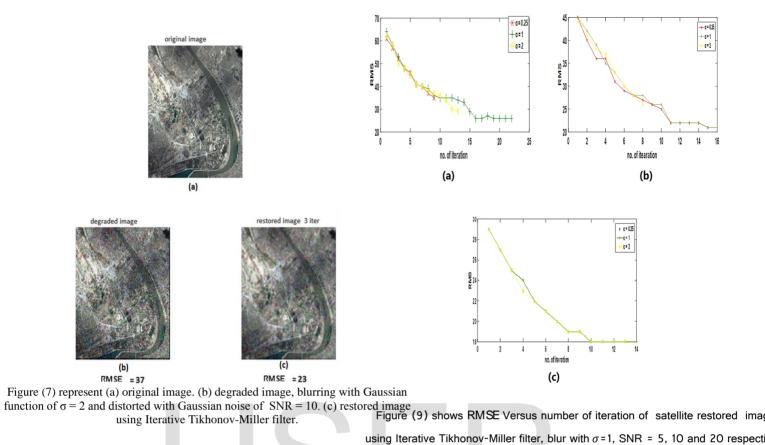
Iterative Tikhonov filter, in which regularization parameter" α " h value α =1 use to Restore the degraded satellite image, blurring w

IJSER © 2016 http://www.ijser.org Gaussian blurring function with different standards deviation value distorted with Gaussian noise with different noise level as shown i following figure.





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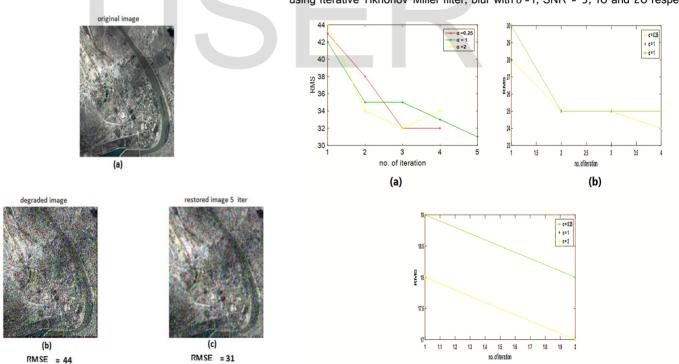


Figure (8) represent (a) original image. (b) degraded image, blurring with Gaus function of $\sigma = 2$ and distorted with Gaussian noise of SNR = 5. (c) restored in

using Iterative Tikhonov-Miller filter.

Figure (10) shows **RMSE** Versus number of iteration of satellite restored image u Iterative Tikhonov-Miller filter, blur with σ =2, SNR = 5, 10 and 20 respectively Figure (9) and (10) show Root mean square error of satellite restoring image decrease with increase the number of iteration for SNR= 5,10 and and Figure (48) show the better curve and good result obtained when,

(c)

regularization parameter of iterative Tikhonov-Miller filter have value equal to 1.

3 RESULT AND DISCUSSION:

From the figuers can be discusses the behavior of Root mean square error with other parameters : Root mean square error of degraded images increase with increase standards deviation values " σ " of Gaussian blurring function and decrease with increasing SNR. And Root mean square error of satellite restored image by using Iterative Tikhonov-Miller filter increase with increase standards deviation values " σ " of Gaussian blurring function and decrease with increase by using Iterative Tikhonov-Miller filter increase with increase standards deviation values " σ " of Gaussian blurring function and decrease with increasing SNR. Figure(10) show Root mean square error for restored images by using Iterative Tikhonov-Miller filter decrease with increase the number of iteration for different signal to noise ratio to certain number of iteration.

4CONCLUSION

The search shows, RMSE of the restored images decreases with increasing the number of iteration until the result convergence and the number of iteration decrease for large degradation parameters with high noise density. The better curve and good result obtained when, the regularization parameter of iterative Tikhonov-Miller filter have value equal to 1. And better restore for less degradation parameters, with high SNR.



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