Intl J Engg Sci Adv Research 2015 Sep;1(3):87-91

Comparative Analysis of 'in vivo' Microscopic Images of Rat Prostate Tissue through Restoration Algorithm

Shiv K.Vaishya
Department of Computer Science & Engineering
Rama University, Kanpur, India
shivjk.it@gmail.com

Vivek Srivastava
Department of Computer Science & Engineering
Rama University, Kanpur, India
viveksrivastavakash@gmail.com

***Abstract*— Image restoration is an important issue in medical imaging. Images are often degraded during the image acquisition process. The degradation may involve blurring, information loss due to sampling, quantization effects, and various sources of noise. The purpose of image restoration is to estimate the original image from the degraded image that minimizes the MSE (Mean Square Error) between them. It is widely used in various fields of applications, such as medical imaging, astronomical imaging, remote sensing, microscopy imaging, photography deblurring, and forensic science, etc. We have *in vivo* prostate tissue of rat after the staining, a technique used in microscopy to enhance contrast in the microscopic image. We have the image of *in vivo p*rostate tissue of rat by administration of specific medicine as the experimental image. In this paper we are giving the comparative results on the prostate tissue after different image restoration techniques like Wiener filter and Geometric mean filter, on the basis of MSE (Mean Square Error), SNR (Signal to Noise Ratio) and PSNR (Peak SNR). After analysis, in term of the MSE, SNR and PSNR, we have the comparative results on the prostate tissue after different image restoration techniques.**

Keywords- Rat Prostate Tissue, in vivo, Staining, Image Restoration, Fourier Spectrum, Point Spread function (PSF), Mean Square Error (MSE), SNR (Signal to Noise Ratio), PSNR (Peak SNR), Motion Blur.

I. INTRODUCTION

Images are produced to record or display useful information. Due to imperfections in the imaging and capturing process, however, the recorded image invariably represents a degraded version of the original scene [15]. Blurring [5, 6, 7, 8] is a form of bandwidth reduction of an ideal image owing to the imperfect image formation process. It can be caused by relative motion between the camera and the original scene, or by an optical system that is out of focus, when aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system, and relative motion between the camera and the ground. Such blurring is not confined to optical images, for example electron micrographs are corrupted by spherical aberrations of the electron lenses, and CT scans suffer from X-ray scatter. In this paper we have used Fourier spectrum method, as a blur identification method which is used to identify the blurs that are presents in the degraded image, which is very useful in the image restoration process. The field of image restoration [9, 10, 11, 12, 13, 14] (sometimes referred to as image deblurring or image deconvolution) is concerned with the reconstruction or estimation of the uncorrupted image from a blurred and noisy one. Essentially, it tries to perform an operation on the image that is the inverse of the imperfections in the image formation system.

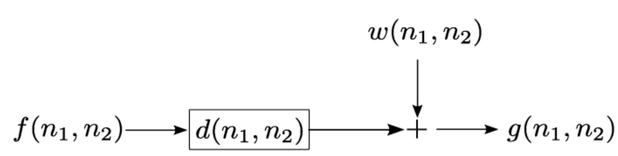
This paper attempts to analyze the brightness of a rat prostate image in Fourier transformed space. The paper is organized as follows: Section 2 and 3 describes Image formation model and Linear Motion Blur, Section 4 and 5 explains the proposed approach of Image Restoration Algorithm and Quantitative Approach. Further Sections 6 and 7 describe the, experimental results and conclusion respectively.

II. IMAGE FORMATION MODEL

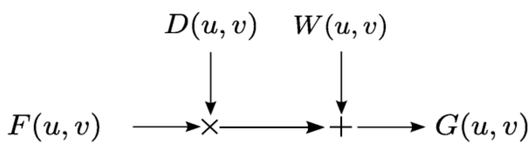
We assume that the blurring function acts as a convolution kernel or point-spread function $d(n_1,n_2)$ that does not vary spatially. It means that the statistical properties (mean and correlation function) of the image and noise do not change spatially. These modeling assumptions can be mathematically formulated as follows. The ideal image $f(n_1,n_2)$ that does not contain any blur or noise, then the recorded image $g(n_1,n_2)$ is modeled as shown in Figure 1a.

$$\begin{aligned} g(n_1,n_2) &= f(n_1,n_2) \otimes d(n_1,n_2) + w(n_1,n_2) \\ &= \sum_{k_1=0}^{N-1}\sum_{k_2=0}^{M-1} d(k_1,k_2)\, f(n_1-k_1,n_2-k_2) + w(n_1,n_2) \end{aligned} \quad (1)$$

Where $w(n_1,n_2)$ is the additive noise that corrupts the ideal image.



(a)



(b)

Fig 1. (a) Image formation model in the spatial domain,
(b) Image formation model in the Fourier domain

The blurring of images is modeled in Fig. 1 as the convolution of an ideal image with a 2-D Point Spread Function (PSF) $d(n_1,n_2)$. The interpretation of (1) is that, if the ideal image $f(n_1,n_2)$ consists of a single intensity point or point source, this point would be recorded as a spread-out intensity pattern $d(n_1,n_2)$, hence the name point spread function. Equation (1) can be rewritten in the frequency domain [1]-[4] as,

$$G(u,v) = F(u,v)D(u,v) + W(u,v) \quad (2)$$

where $D(u,v)$ is the Fourier transform of the PSF (called the optical Transfer function or OTF).

III. LINEAR MOTION BLUR

It occurs due to the relative motion between the camera and the scene, i.e. the object moved during the time that the shutter was open, with the result that the object appears to be smeared in the recorded image. Obviously we obtain precisely the same effect if the camera moved while the shutter was open. When the scene to be recorded, translates relative to the camera at a constant velocity $v_{relative}$ under an angle of Φ radians with the horizontal axis during the exposure interval [0, $t_{exposure}$], the distortion is one-dimensional. Defining the "length of motion" by $L = v_{relative} \cdot t_{exposure}$, then the PSF is given by:

$$d(x,y;L,\phi) = \begin{cases} \frac{1}{L}; & if \sqrt{x^2+y^2} \le \frac{L}{2} \; and \; \frac{x}{y} = -\tan\phi \\ 0; & elsewhere \end{cases} \quad (1)$$

The discrete version of (3) is not easily captured in a closed form expression in general. For the special case that Φ=0, an appropriate approximation is:

$$d(n_1,n_2;L) = \begin{cases} \frac{1}{L}; & if\; n_1 = 0, |n_2| \le \left\lfloor \frac{L-1}{2} \right\rfloor \\ \frac{1}{2L}\left\{(L-1) - 2\left(\frac{L-1}{2}\right)\right\}; & if\; n_1 = 0, |n_2| = \left\lceil \frac{L-1}{2} \right\rceil \\ 0; & elsewhere \end{cases} \quad (2)$$

IV. IMAGE RESTORATION ALGORITHM

A. Inverse Filter

From equation (1), if noise is not present in the observed image then the recorded image can be modeled as

$$g(n_1,n_2) = d(n_1,n_2) \otimes f(n_1,n_2) \quad (3)$$

Its Fourier transform gives,

$$G(u,v) = D(u,v)F(u,v)$$
$$\hat{F}(u,v) = \frac{G(u,v)}{D(u,v)} \quad (4)$$

i. e., by modeling the degenerating effect (d) and dividing the FT of the image by the FT of the model, then we can get the FT of the restored image. If noise is present in the observed image then we get

$$g(n_1,n_2) = d(n_1,n_2) \otimes f(n_1,n_2) + w(n_1,n_2) \quad (5)$$

Its Fourier transform gives,

$$G(u,v) = D(u,v)F(u,v) + W(u,v)$$
$$F(u,v) = \frac{G(u,v)}{D(u,v)} - \frac{W(u,v)}{D(u,v)} \quad (6)$$

B. Wiener Filter

To overcome the noise sensitivity of the inverse filter, a number of restoration filters have been developed that are collectively called least-squares filters [16, 17]. We describe the two most commonly used filters from this collection, namely the Wiener filter and the constrained least-squares filter. The Wiener filter is a linear spatially invariant filter to choose an estimate $\hat{f}$ of the uncorrupted image f such that it minimizes the mean-squared error (MSE) between the ideal and the restored image.

$$MSE = E\left[\left(f(n_1,n_2) - \hat{f}(n_1,n_2)\right)^2\right]$$
$$\approx \sum_{n_1=0}^{N-1}\sum_{n_2=0}^{M-1}\left(f(n_1,n_2) - \hat{f}(n_1,n_2)\right)^2 \quad (7)$$

The solution of this minimization problem is known as the Wiener filter. It removes the additive noise and inverts the blurring simultaneously so as to emphasize any lines which are hidden in the image. This filter operates in the Fourier domain, making the elimination of noise easier as the high and low frequencies are removed from the noise to leave a sharp image. Using Fourier transforms means the noise is easier to completely eliminate and the actual line imbedded in noise easier to isolate making it a slightly more effective method of filtering. The Wiener filter in Fourier domain can be expressed as follows:

$$\begin{aligned} F(u,v) &= \left[\frac{D^*(u,v).S_f(u,v)}{S_f(u,v)|D(u,v)|^2 + S_\eta(u,v)}\right].G(u,v) \\ &= \left[\frac{D^*(u,v)}{|D(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right].G(u,v) \\ &= \left[\frac{1}{D(u,v)}\frac{|D(u,v)|^2}{|D(u,v)|^2 + S_\eta(u,v)/S_f(u,v)}\right].G(u,v) \end{aligned} \tag{8}$$

Where D(u, v) = degradation function.
$D^*(u, v)$ = complex conjugate of D(u, v).

$$|D(u,v)|^2 = D^*(u,v).D(u,v)$$

$S_\eta(u,v) = |W(u,v)|^2$ = power spectrum of the noise and $S_f(u,v) = |F(u,v)|^2$ = power spectrum of ideal (original) image.

When noise is zero, Wiener Filter = inverse Filter.

Since $S_\eta(u,v) = |W(u,v)|^2$ and $S_f(u,v) = |F(u,v)|^2$ are seldom known, the Wiener Filter is frequently approximated by

$$F(u,v) = \left[\frac{1}{D(u,v)}\frac{|D(u,v)|^2}{|D(u,v)|^2 + K}\right].G(u,v) \tag{9}$$

Where K is specified as a constant.

4.3 Geometric Mean Filter

Geometric mean filter is the generalization of the wiener fiter.The Geometric mean filter in Fourier domain can be expressed as follows:

$$F(u,v) = \left[\frac{D^*(u,v)}{|D(u,v)|^2}\right]^\alpha . \left[\frac{D^*(u,v)}{|D(u,v)|^2 + \beta.\left(S_\eta(u,v)/S_f(u,v)\right)}\right]^{1-\alpha} .G(u,v) \tag{10}$$

Where α and β are positive and real constant.

When α = 1 this filter reduces to the inverse filter, with α = 0 the filter becomes parametric wiener filter, which reduces to the standard wiener filter when β =1. If α =1/2, the filter becomes a product of the two quantities raised to the same power, which is the definition of Geometric mean filter. When α < 1/2 and β = 1 then the filter performance will tend toward inverse Filter similarly, when α > 1/2 and β =1, the filter performance tend toward Wiener Filter. When α =1/2 and β =1 then the filter is referred to as the spectrum equalization Filter.

V. QUANTITATIVE APPROACH

A. Mean Square Error (MSE)

The mean square error (MSE) between the original image $f(x,y)$ and filtered image $\hat{f}(x,y)$ of size M X N, can be calculated as-

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left\{\hat{f}(x,y) - f(x,y)\right\}^2 \tag{11}$$

B. Signal to Noise Ratio (SNR)

In image restoration, the improvement in quality of the restored image over the recorded blurred one is measured by the signal-to-noise-ratio improvement. The signal-to-noise-ratio [7] of the recorded (blurred and noisy) image is defined as follows in decibels:

$$SNR_g = 10.\log_{10}\left(\frac{\text{variance of the ideal image } f(n_1,n_2)}{\text{variance of the difference image } g(n_1,n_2) - f(n_1,n_2)}\right)(dB)$$

The signal-to-noise-ratio of the restored image is similarly defined as:

$$SNR_{\hat{f}} = 10.\log_{10}\left(\frac{\text{variance of the ideal image } f(n_1,n_2)}{\text{variance of the difference image } \hat{f}(n_1,n_2) - f(n_1,n_2)}\right)(dB)$$

$$SNR = 10\log_{10}\left(\frac{\sigma^2}{\sigma_e^2}\right) \tag{12}$$

Where σ^2 is the variance of the desired image and σ^2_e is the variance of the difference image.

C. Peak Signal to Noise Ratio (PSNR)

The metric Peak Signal to Noise Ratio (PSNR) [14] which relates the magnitude of the noise to the peak value in the image, in decibels, is defined as,

$$PSNR = 10\ log_{10}\left\{\frac{P^2}{MSE}\right\}dB \tag{13}$$

Where p is the peak intensity value of a signal (i.e. 255 is the peak value in an 8-bit image).

VI. EXPERIMENTAL RESULTS

In table-1(A), we have shown the image analysis of prostate tissue in case of motion blur of length 7 pixels and angle 30^0. The original image of prostate tissue is given in figure 2(a). The power spectrum of figure 2(a) is given in figure 2(b) and its histogram plot is given in figure 2(c). Using MATLAB software, we are generated a degraded image after introducing a motion blur in length 7 pixels and angle 30^0 which are shown in figure 2(d) and its power spectrum (of figure 2(d)) is given in figure 2(e). The restored image are shown in figure 2((f), (g) & (h))) after applying the various restoration algorithm such as Wiener Filter and Geometric mean filter on the degraded image of figure 2 (d). These restoration filters have better restored image and its comparative performance using quantitative approach (MSE, SNR & PSNR) are given in table -1 (B). From table -1(B), we see that the degraded image have MSE - 0.011900, SNR-

14.779509 and PSNR-19.2445 after applying the Wiener filter we get the MSE - 0.006473, SNR-20.167760 and PSNR - 21.8889 and after applying the Geometric mean filter we get the MSE - 0.000922, SNR-35.145876 and PSNR-30.3537, after seeing these data we can say that geometric mean filter have smallest MSE and highest SNR and PSNR value, this means it has better restored image in comparison of other restoration algorithm.

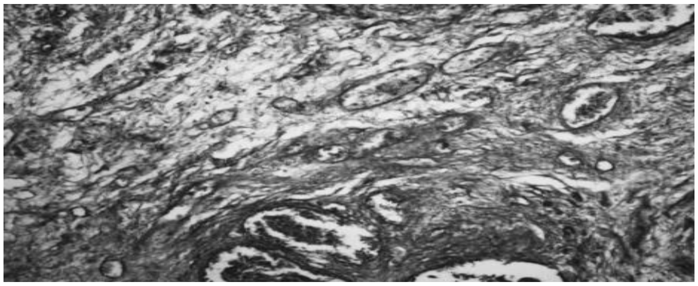
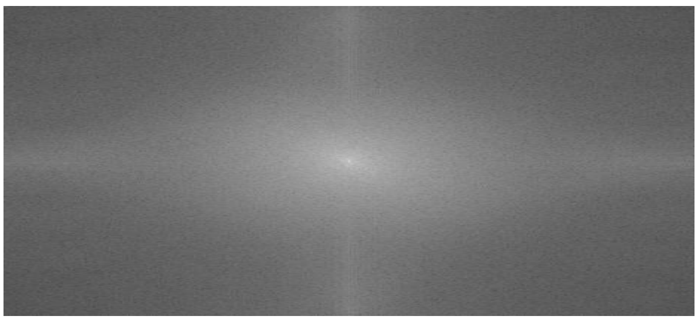
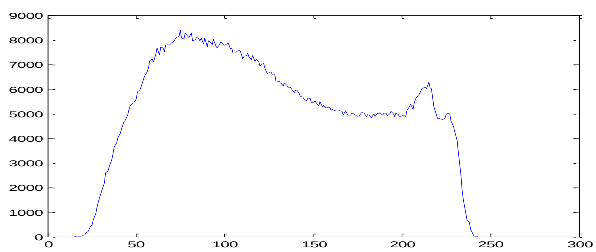


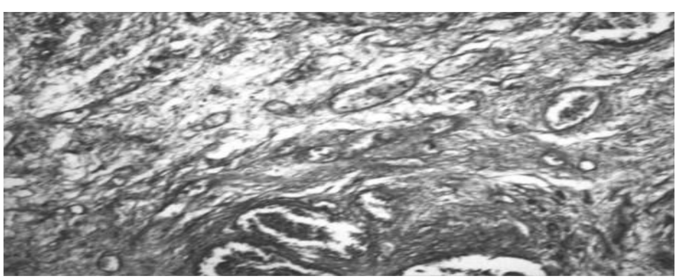
Fig2(a). Image of Prostate Tissue of Rat



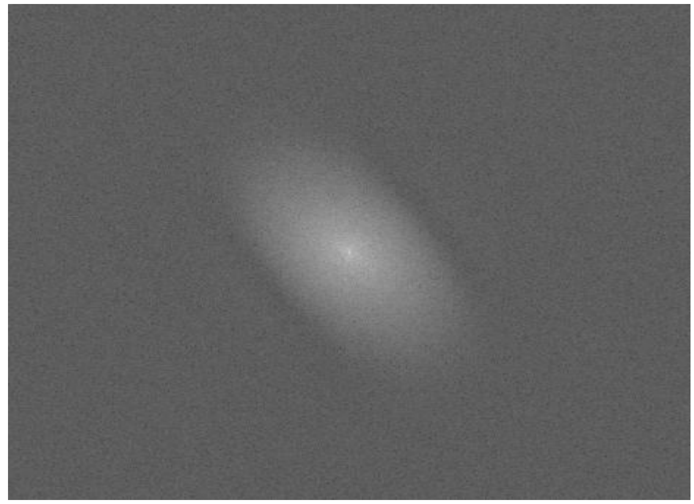
(b). Power spectrum of Fig.2(a)



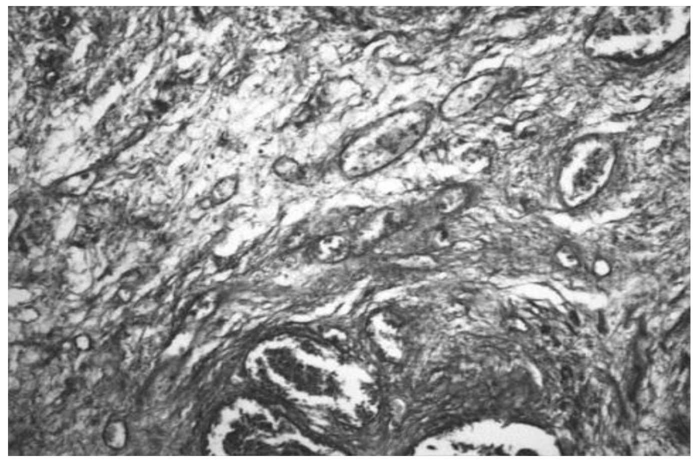
(c). Histogram plot of Fig.2 (a)



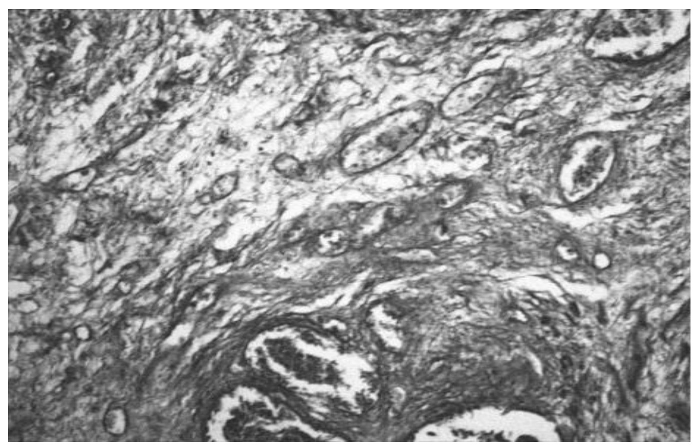
(d). Degraded Image (with random noise & motion Blur) of fig.2(a)



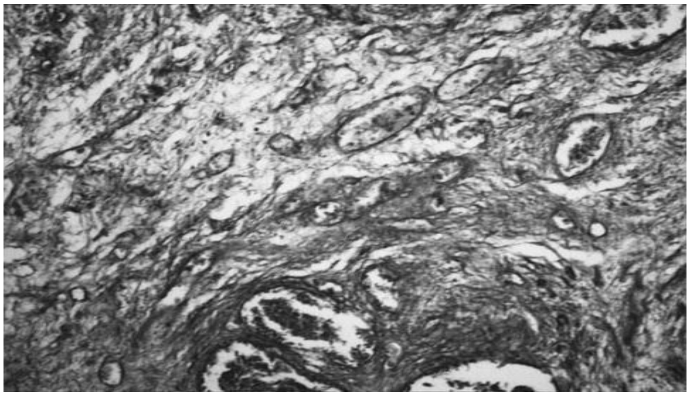
(e). Power spectrum of fig.2(d)



(f). Restored Image (with parametric wiener Filter) of fig.2(d)



(g). Restored Image (with constant wiener Filter) of fig.2(d)



(h). Restored Image (with Geometric Mean Filter) of fig.2(d)

TABLE-1 (B)

MEASURE PERFORMANCE OF RESTORATION ALGORITHM USING QUANTITATIVE APPROACH IN CASE OF MOTION BLUR OF LENGTH 7 PIXELS AND ANGLE 30^0

Filter	Mean Square Error (MSE)	Signal to Noise Ratio (SNR)	Peak Signal to Noise Ratio (PSNR)
Before Filter (Degraded Image)	0.011900	14.779509	19.2445
Wiener Filter *parametric	0.006473	20.167760	21.8889
Wiener Filter *constant	0.008201	17.680091	20.8614
Geometric Mean Filter	0.000922	35.145876	30.3537

VII. CONCLUSIONS

The geometric mean filter gives the better result in comparison of other restoration filtering techniques. The geometric mean filter have smallest MSE-0.000922 and highest SNR-35.1459dB and PSNR-30.3537dB in case of motion blur in comparison of MSE, SNR and PSNR values of other restoration filter.

ACKNOWLEDGEMENT

We are very much thankful to Prof. Harish Kumar (Dean, FET, Rama University) for useful discussion and our Chancellor, Dr. B. S. Kuswaha (Rama University) for providing the space and resources to carry out the research work in the college. Also, we thanks to Dr. Gopal Gupta, Senior Scientist, CDRI, Lucknow for providing the rat tissue from the animal house for the analysis of the administrated medicines on Prostate tissue and its effect.

REFERENCES

[1] H. Akaike "Power Spectrum Estimation through Autoregression Model Fitting", Annals of the Institute of Statistical Mathematics,vol.21,pp.407-419,1969.

[2] H.Akaike, "A New Look at the Statistical Model Identification",IEEE Trans. Autom. Control, vol.AC-19,pp.716-723,1974.

[3] A. M. Aibinu, Momoh J. E. Salami,A. A.Shafie and A. R. Najeeb, "MRI Reconstruction Using Discrete Fourier Transform:A tutorial",World Academy of Science, Engineering and Technology 42, pp. 179-185, 2008.

[4] R. Neelamani, H. Choi, and R. G. Baraniuk, "Forward: Fourier-wavelet regularized deconvolution for ill-conditioned systems", IEEE Trans. on Signal Processing, Vol. 52, No 2, pp. 418-433, 2003.

[5] I. Aizenberg, T. Bregin, C. Butakoff, V. Karnaukhov, N. Merzlyakov and O. Milukova, "Type of Blur and Blur Parameters Identification Using Neural Network and Its Application to Image Restoration". In J.R. Dorronsoro (ed.) Lecture Notes in Computer Science, Springer-Verlag, Vol. 2415, pp. 1231-1236, 2002.

[6] M.R. Banham and A. K. Katsaggelos. "Digital Image Restoration. "IEEE Signal Processing Magazine, vol.14, no.2, pp.24-41, March 1997.

[7] R. L. Lagendijk and J. Biemond, "Basic Methods of Image Restoration and Identification", Information and Communication Theory Group, pp. 1-25, Feb 15, 1999.

[8] R.L.Lagendijk, J. Biemond and D.E. Boekee, "Identification and Restoration of Noisy Blurred Images Using the Expectation-Maximization Algorithm", IEEE Trans. on Acoustics, Speech and Signal Processing;38, 1990.

[9] R. C. Gonzalez and R.E. Wood, Digital Image Processing, Prentice-Hall, India, Second Edition, 2007.

[10] A. K. Jain, Fundamental of Digital Image Processing, University of California, Davis, Prentice Hall of India Private Limited, New Delhi-110001, 2007.

[11] A. M. Aibinu, Momoh J. E. Salami,A. A.Shafie and A. R. Najeeb, "MRI Reconstruction Using Discrete Fourier Transform: A tutorial", World Academy of Science, Engineering and Technology 42, pp. 179-185, 2008.

[12] Jagadish H. Pujar and Kiran S. Kunnur, "A Novel Approach for Image Restoration Via Nearest Neighbor Method", Journal of Theoretical and Applied information Tech., Vol.14, No.2, pp.76-79, April-2010.

[13] S. K. Satpathy, S. Panda, K. K. Nagwanshi and C. Ardil," Image Restoration in Non-Linear Filtering Domain using MDB approach", International Journal of Information and Communication Engineering, Vol.6, No. -1, pp-45-49, 2010.

[14] S. S. Al-amri, N.V. Kalyankar and S.D. Khamitkar, "A Comparative Study of Removal Noise from Remote Sensing Image", IJCSI International Journal of Computer Science Issues, 7(1) pp. 32-36, January 2010.

[15] B. R. Hunt, "Digital image processing," Proc. IEEE, vol. 63, pp.693-708, Apr. 1975.

[16] D. Slepian, "Least-squares filtering of distorted images", J. Opt. Soc.America.,vol.57, pp 918-922, 1967.

[17] K. Von Heide, "Least Squares image restoration", Opt. Communication, vol. 31, pp 279-284, 1979.