# Development Of A Modified Wiener Algorithm In The Restoration Of Digital Images

Oke Alice O, Omidiora Elijah O, Fakolujo Olaosebikan A.

**Abstract**: Digital image processing has made its way into today's technology and Computer driven Society with applications encompassing a wide variety of specialized disciplines. Image degradation, however, becomes a serious threat to image processing as current trend in security measures tends towards the use of biometrics. Moreover, data collected using image sensors are generally contaminated by noise and region of interest in the image degraded by many factors among which is motion blur during acquisition, thus, the need to recover or reconstruct the original image. Several image restoration algorithms have been developed to minimize such errors. Wiener filtering algorithm has been and still being adjudged the best restoration algorithm for the clas of linear methods. However, it has the tendency to cause undesirable artifacts in the resultant image. In order to remove the undesirable artifacts, this paper developed a modified Wiener algorithm. Performance of which was evaluated and Computational results showed modified Wiener performed better than the conventional Wiener algorithm.

**Index Terms**: Convolution, Degradation, Restoration, Simulation, Wiener Algorithm.

## 1 INTRODUCTION

Image processing operates on images and produces images as output, with changes intended to improve the visibility of features or to make the images better for printing or transmission, or to facilitate subsequent analysis. Images are, however, degraded by object or camera motion and noise during image acquisition and this affects the quality of the image. Consequently, it deteriorates the effectiveness of object recognition, event detection and visual perception. Image restoration is used to remove or minimize this degradation. The key to image restoration is to model the degradation and then to use an inverse operation to reverse it [15]. The recovery of an original image from degraded observations is of crucial importance and finds application in several scientific areas including medical imaging and diagnosis [7], military [14], surveillance [4], satellite and astronomical imaging [9], and remote sensing [23]. A number of various algorithms have been proposed based on the class of restoration technique. There are eight image restoration techniques, Continuous Image Spatial Filtering Restoration is the method for the class of imaging systems in which the spatial degradation can be modeled by a linear-shift-invariant impulse response and the noise is additive, restoration of continuous images can be performed by linear filtering techniques [21]. Under this class there is Inverse filtering, Wiener filtering and Parametric estimation filtering methods. The simplex method for reconstructing a degraded image is the use of inverse filtering method which inverts the degraded function of the system to yield a restored image [21]. This method will however not produce a perfect reconstruction in the presence of noise. Improved restoration quality is possible with Wiener filtering technique because it alleviates noise problem inherent to inverse method [19]. Wiener filtering method has since been adjudged as the best restoration algorithm for the class of linear methods under the suitable condition of addictive Gaussian noise. Early efforts in the application of Wiener method was geared towards magnetic fields that were contaminated by noise [10], improving signal-to-noise and resolution in acoustic images [20], magnetic profiling in the volcanic environment of Mt. Etna [5], image and video denoising [19], Ju, Hua, Jiande and Daizhen, [13] combined it with SAR to estimate a single high-resolution image from different low-resolution images. However, it has the tendency to cause undesirable artifacts in the resultant image. Also, Gaussian noise has been the default noise model and suitable condition for Wiener restoration algorithm [24]. Other algorithms such as constraint least square filter and geometric filter have been proposed to remove the undersirable artifacts but whose performance either tends to inverse or Wiener filtering method [9]. In this paper, a modified Wiener restoration technique was proposed by hybridizing Constrained least error method and parametric restoration algorithm aimed at reconstruction images that have been degraded by Gaussian noise and linear motion blur. The performance of the modified Wiener restoration algorithm was evaluated using quantitative performance measures of root mean square error (RMSE), signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR). Computational result showed that modified Wiener performed better than the conventional Wiener algorithm.


- *A.O.Oke is with the Computer Science and Engineering Department, Ladoke Akintola University of Technology, Ogbomoso, Oyo State. Nigeria.*
- *E.O.Omidiora is with the Computer Science and Engineering De-partment, Ladoke Akintola University of Technology, Ogbomoso, Oyo State. Nigeria.*
- *O.A.Fakolujo is with the Electrical and Electronics Engineering Department, University of Ibadan, Ibadan, Oyo State, Nigeria.*
- *alitemi2006@yahoo.com, eoomidiora@lautech.edu.ng, ola@fakolujo.com*


## 2 LINEAR MOTION BLUR

Motion blur is an effect you will see in photographs of scenes where objects are moving. It is mostly noticeable when the exposure is long, or if objects in the scene are moving rapidly. Many types of motion blur can be distinguished all of which are due to relative motion between the recording device and the scene. This can be in the form of a translation, a rotation, a sudden change of scale, or some combinations of these [17]. It is defined by the Point Spread Function (PSF) given by (1).

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

### 2.1 Noise Model
Noise is any undesired information that contaminates an image. Noise appears in images from variety of sources. The digital image acquisition process, which converts an optical image into a continuous electrical signal that is then sampled, is the primary process by which noise appears in digital images [24]. At every step in the process there are flunctuation caused by natural phenomena that add a random value to the exact brightness value of a pixel. Images are prone to different types of noise some of which are: Gaussian, Salt and Pepper, Speckle, Poisson, Rayleigh, Erlang, Exponential, Uniform, Periodic [15]. Gaussian Noise is the most common and occurs in all recorded images to a certain extent. It is due to the discrete nature of radiation that is the fact that each imaging system is recording an image by counting photons. This noise can be modeled with an independent, additive model, where the noise has a zero-mean Gaussian distribution described by its standard deviation (σ) or variance [14]. This means that each pixel in the noisy image is the sum of the true pixel value and a random, Gaussian distributed noise value. The probability density function is described by (2).

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}} \qquad (2)$$

where $\boldsymbol{\sigma^2}$ = Variance, $\boldsymbol{x}$ = is the gray level and $\boldsymbol{\mu}$ = mean value.

### 2.2 Convolution
In mathematics, specifically, functional analysis, convolution is a mathematical operation on two functions *f* and *g*, producing a third function that is typically viewed as a modified version of one of the original functions [1]. Linear filtering of an image is accomplished through convolution. Here, convolution is a neighborhood operation in which each output pixel is the weighted sum of neighboring input pixels. The matrix of weights is called the convolution kernel, also known as the filter [25].

## 3. ANALYTICAL TECHNIQUES
A blurred or degraded image is approximately described by the (3).

$$F_0(x,y) = F_1(x,y) \otimes H_D(x,y) + N(x,y) \qquad (3)$$

where $F_0(x,y)$ is the degraded (blurred and noisy) image, $F_1(x,y)$ is the original image, which represents the image obtain under a perfect image acquisition condition, in this case the input image. $H_D(x,y)$ is the distortion operator, also called the PSF. When the distortion operator is convolved with the image, it creates the distortion. $N(x,y)$ is the additive noise which is introduced during image acquisition, that corrupts the image [21], [16]. After restoration with this filter, the reconstructed image is represented by the (4).

$$\hat{F}_1(x,y) = F_0(x,y) \otimes H_R(x,y) \qquad (4)$$

Where $\hat{F}_1(x,y)$is the restored image, $F_0(x,y)$ is the degraded image and $H_R(x,y)$ is the restoration filter. From (3) and (4).

$$\hat{F}_1(x,y) = [F_1(x,y) \otimes H_D(x,y) + N(x,y)] \otimes H_R(x,y) \qquad (5)$$

Fig1.ps shows a typical image restoration model, giving (3) and (4) in graphical form. This technique was applied to discrete images, each of the spectral functions involved in the filtering operation was replaced by its discrete two dimensional Fourier transform counterpart of (6). Fourier transform is important because convolution in spatial domain and multiplication in frequency domain constitutes a Fourier transform pair. Hence, (5) in the Fourier transform has the advantage of short computation time to produce solution [9].

$$\hat{\mathcal{F}}_1(\omega_x,\omega_y) = [\mathcal{F}_1(\omega_x,\omega_y)\mathcal{H}_D(\omega_x,\omega_y) + \mathcal{N}(\omega_x,\omega_y)]\mathcal{H}_R(\omega_x,\omega_y) \qquad (6)$$

where $\hat{\mathcal{F}}_1(\omega_x,\omega_y)$, $\mathcal{F}_1(\omega_x,\omega_y)$, $\mathcal{H}_D(\omega_x,\omega_y)$, $\mathcal{N}(\omega_x,\omega_y)$ and $\mathcal{H}_R(\omega_x,\omega_y)$ are the two-dimensional Fourier transforms of $\hat{F}_1(x,y)$, $F_1(x,y)$, $H_D(x,y)$, $N(x,y)$ and $H_R(x,y)$ respectively.

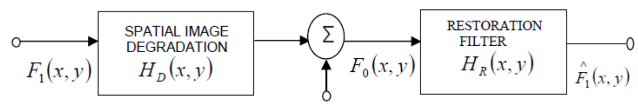



**Fig.1.** Image Restoration Model

### 3.1 Inverse Filtering Method
Inverse filtering concept inverts the PSF of the degrading system to yield a restored image [3], [19], [21]. The restoration inverse filter PSF is chosen so that

$$\mathcal{H}_R(\omega_x,\omega_y) = \frac{1}{\mathcal{H}_D(\omega_x,\omega_y)} \qquad (7)$$

then the spectrum of the reconstructed image becomes

$$\hat{\mathcal{F}}_1(\omega_x,\omega_y) = \mathcal{F}_1(\omega_x,\omega_y) + \frac{\mathcal{N}(\omega_x,\omega_y)}{\mathcal{H}_D(\omega_x,\omega_y)} \qquad (8)$$

Inverse filtering will however not produce a perfect reconstruction in the presence of noise but if source noise is present, there will be an additive reconstruction error whose value can become quite large at spatial frequencies for which $\mathcal{H}_D(\omega_x,\omega_y)$ is small [6]. Another fundamental difficulty with inverse filtering is that the transfer function of the degradation may have zeros in its passband, which makes the inverse filter not physically realizable, and therefore the filter must be approximated by a large value response at such points.

### 3.2 Constrained Least-square Error Filter
Constrained least-square error filter and Parametric filter [6] were proposed in a bid to further alleviate noise. Taking into account the noise influence on inverse filter, a linear function of the estimated image can be minimized under a constraint [11] related to the noise as (9)

$$\varepsilon^2 = \epsilon\left(L * \hat{f}_1(x,y)\right)^2 \qquad (9)$$

With

$$\epsilon\left(f_1(x,y) - h * \hat{f}_1(x,y)\right)^2 = \sigma_N{}^2 \qquad (10)$$

The restoring filter in Fourier transform is (11), [17], [21].

$$\mathcal{H}_R(\omega_x,\omega_y) = \left[\frac{\mathcal{H}_D * (\omega_x,\omega_y)}{|\mathcal{H}_D(\omega_x,\omega_y)|^2 + \gamma\,|L(\omega_x,\omega_y)|^2}\right] \quad (11)$$

Where $\gamma$ is adjusted to satisfy Equation (10). $\gamma$ in (11) is a design constant and $L(\omega_x,\omega_y)$ is a design spectral variable. If $\gamma$ = 1 and $|L(\omega_x,\omega_y)|^2$ are set equal to the spectral ratio of Wiener Equation, "Equation (11) becomes equivalent to the Wiener filter". If there is no blurring of the ideal image, $\mathcal{H}_D(\omega_x,\omega_y) = 1$, the Wiener filter becomes the inverse filter. One of the various choices that have also been proposed for $L(x,y)$ is (12) and the restoration filter is (13), [6].

$$L(x,y) = \left(\frac{S_N(x,y)}{S_{F_1}(x,y)}\right)^{\frac{1}{2}} \quad (12)$$

$$H_R(x,y) = \frac{H_D{}^*(x,y)}{|H_D(x,y)|^2 + \gamma\frac{S_N(x,y)}{S_{F_1}(x,y)}} \quad (13)$$

This filter tries to minimize the energy of the gradient of the estimated image, it thus limits the effect of the noise. This minimization of the energy of the restored image is weighted by the confidence reposed in the restored image. This confidence is measured through the signal to noise ratio. When $\gamma$ varies from 0 to 1 this filter varies from the inverse filter to the Wiener filter [6].

### 3.3 Parametric Filter

Another approach is in forcing the spectrum of the restored image to be equal to the spectrum of the input image

$$S_{F_1}(x,y) = |H_R(x,y)|^2 S_{F_2} \quad (14)$$

Thus

$$S_{F_1}(x,y) = |H_R(x,y)|^2\{|H_D(x,y)|^2 S_{F_1}(x,y) + S_N(x,y)\} \quad (15)$$

Where $S_{F_2}$ in (14) equals $|H_D(x,y)|^2 S_{F_1}(x,y) + S_N(x,y)$ in (15). Enforcing this spectrum to be equal to $S_{F_1}(x,y)$ leads to the restoration filter of (16) in the Fourier transform [6], [2].

$$\mathcal{H}_R(\omega_x,\omega_y) = \left[\frac{H_D{}^*(x,y)}{|H_D(x,y)|^2 + \frac{S_N(x,y)}{S_{F_1}(x,y)}}\right]^{1/2} \quad (16)$$

Equation (16) takes into consideration the geometric mean between the inverse and the Wiener filter. Equation (17) is the generalized form of (16).

$$\mathcal{H}_R(\omega_x,\omega_y) = \left[\frac{H_D{}^*(x,y)}{|H_D(x,y)|^2 + \gamma\frac{S_N(x,y)}{S_{F_1}(x,y)}}\right]^{\alpha} \quad (17)$$

Equations (13) and (16) are termed parametric filters, they are seen as variant of Wiener filter. Though these filters are found to be good but have not measured to the performance of Wiener filtering in restoration. Their performance either tend to Inverse or Wiener filter [21].

### 3.4 Wiener Filter

Improved restoration quality is possible with Wiener filtering techniques, because it alleviates noise problems inherent to inverse filtering by incorporating *apriori* statistical knowledge of the noise field [21]. The Wiener filter is a linear spatially invariant filter of the form of (3). Its PSF, $\mathcal{H}_D(\omega_x,\omega_y)$ is chosen such that it minimizes the mean-square restoration error (MSE) between the input and the restored image. This criterion attempts to make the difference between the original image and the restored one, that is, the remaining restoration error which should be as small as possible on the average:

$$MSE = E\left[\left(f_1(x,y) - \hat{f}_1(x,y)\right)^2\right] \approx \sum_{x-0}^{X-1}\sum_{y-0}^{Y-1}\left(f_1(x,y) - \hat{f}_1(x,y)\right)^2 \quad (18)$$

The solution of the minimization problem of (18) is known as the Wiener filter, and is defined as:

$$H_R(x,y) = \frac{H_D{}^*(x,y)}{|H_D(x,y)|^2 + \frac{S_N(x,y)}{S_{F_1}(x,y)}} \quad (19)$$

where $H_D{}^*(x,y)$ is the complex conjugate of $H_D(x,y)$, $S_N(x,y)$ is the power spectrum of the noise, $S_{F_1}(x,y)$ is the power spectrum of the input and $H_R(x,y)$ is as previously defined. This filter is convolved with the degraded image to give a restored image [8]. The power spectrum is a measure for the average signal power per spatial frequency $(x,y)$ carried by the image. The noise is assumed to be uncorrelated, so its power spectrum is determined by the noise variance only given in (23), [17].

$$S_N(x,y) = \sigma_N{}^2 \quad (20)$$

The power spectrum of the input image is estimated from the power spectrum of the degraded image and compensated for the variance of the noise, this is given as (21).

$$S_{F_{11}}(x,y) \approx S_{F_1}(x,y) - \sigma_N{}^2 \approx \frac{1}{MN}H_D{}^*(x,y)H_D(x,y) - \sigma_N{}^2 \quad (21)$$

### 3.5 Modified Wiener Filtering Model

The Constrained least-square error filter yields a smoother restoration but its deblurring is not as effective as that of Wiener technique [18]. Parametric filter performance tend towards Wiener's and due to the undesirable artifacts in the resultant image produced from Wiener technique, a need arises to modify Wiener in order to further minimize the error and improve on the resultant image [24]. Equation (22) is the hybridization of constrained least-square error and the parametric filters. Hence, the advantage of the smoother restoration of the constrained least-square error filter and the property of the parametric filter with $\alpha$ and $\gamma$ as the two tuning parameters [6] were combined to arrive at (25).

$$H_R(x,y) = \left(\frac{H_D{}^*(x,y)}{|H_D(x,y)|^2 + \gamma\frac{S_N(x,y)}{S_{F_1}(x,y)}}\right) * \left(\frac{H_D{}^*(x,y)}{|H_D(x,y)|^2 + \gamma\frac{S_N(x,y)}{S_{F_1}(x,y)}}\right)^{1/2} \quad (22)$$

Let

$$X = \frac{H_D^*(x,y)}{|H_D(x,y)|^2 + \gamma \frac{S_N(x,y)}{S_{F_1}(x,y)}} \quad (23)$$

Therefore

$$H_R(x,y) = X^{3/2} \quad (24)$$

Hence

$$H_R(x,y) = \left(\frac{H_D^*(x,y)}{|H_D(x,y)|^2 + \gamma \frac{S_N(x,y)}{S_{F_1}(x,y)}}\right)^{3/2} \quad (25)$$

## 4. MATERIALS AND METHOD

The proposed algorithm was carried out on a Compaq Presario CQ60 notebook PC with typical specification of an AMD Athlon Dual-Core QL-62 GHz processor board, 32-bit Window Vista operating system and 2.00GB Ram using Image processing tools of MATLAB (version 7.9.0.529 (R2009b)). The first phase was the acquisition of data, which is achieved by making use of direct imaging system. A Canon Powershot SD400 was the digital camera (with effective pixels of approximately 5.0 million, image sensor of ½.5-inch CCD and lens of 5.8 (W) – 17.4 (T) mm) used for the parallel acquisition tagged real while Photosmart 330 scanner was used for serial acquisition tagged scanned. Samples of various sizes were collected through the two sources. The data obtained from the sampled image was required in the modelling of the degradation. Simulation of the linear motion blur was first carried out using (1). Linear motion blur was employed because the restoration system being considered is of a linear-shift-invariant filter defined by the impulse response. This process was performed by creating a PSF that simulated the blur which is required to degrade the image. The blur was implemented by first creating a PSF filter which approximates the linear motion blur. This PSF was then convolved with the input image and the blurred image was produced. The amount of blur generated is a function of the length of the blur (in pixels) and the angle of the blur. These parameters were altered to generate variations of blur, and ultimately a length of 31 pixels at an angle of 11 degrees were found to generate sufficient motion blur to the image. Gaussian noise was introduced to the blurred image and the developed restoration algorithm was then applied on the degraded image $\gamma$ being varied. This was convolved with the blurred and noisy image to remove the blur and noise, the optimum restoration was found at $\gamma = 0.95$. The performance of the developed restoration algorithm was evaluated based on three statistical measurements, RMSE, SNR and PSNR "[26]". These parameters were used to determine the rate of restoration with the noise variance varied from 0.0001 to 0.01. Results from restoration with the developed algorithm were evaluated with Wiener algorithm. Restoration of blurred and noisy images acquired from parallel acquisition was also compared with that of serial acquisition. The SNR of the blurred and noisy image is defined as follows in decibels:

$$= 10\log_{10}\left(\frac{\sigma \text{ of difference in image } f_0(x,y) - f_1(x,y)}{\sigma \text{ of difference in image } \hat{f}_1(x,y) - f_1(x,y)}\right) \quad (26)$$

The improvement in SNR is basically a measure that expresses the reduction of disagreement with the input image when evaluating the distorted and restored image. The Mean Square Error (MSE) is the average error per pixel and the RMSE is the square root of the MSE. "Equation (27) indicates the formula for RMSE".

$$RMSE = \sqrt{\frac{\sum\left(f_1(x,y) - \hat{f}_1(x,y)\right)^2}{M \times N}} \quad (27)$$

$$PSNR = 20\log_{10}\frac{255}{RMSE} \quad (28)$$

## 5. RESULTS AND DISCUSSION

An appreciable removal of the noise and blur was observed when the modified Wiener algorithm was applied to the degraded image. However, it was not possible to obtain perfect reconstruction because ideal image is not usually available in practice that would have provided the properties for correct measurement [22], as presented under Wiener algorithm. Fig2.ps to fig4.ps represent the graph of RMSE, SNR and PSNR respectively against variance for the restoration of real degraded image for Wiener and Modified Wiener algorithms. In Fig2.ps, Modified Wiener has lower values of RMSE compared with that of Wiener algorithm for all values of the variance considered. This shows an improvement of Modified Wiener algorithm over Wiener. The least value of RMSE was found at variance value 0.0002 for both Wiener and modified Wiener. This is in contrast to 0.0001 found in [22]. This implies that the error in variance value 0.0001 is not the least, that the system was discovered to have higher noise immunity. Fig3.ps and fig4.ps showed modified Wiener having higher SNR and PSNR than Wiener algorithm for all values of variance considered except at 0.0009 where both algorithms have the same PSNR according to the experiment carried out which is as shown in Fig4.ps. The highest SNR value on fig3.ps coincided with variance value 0.01 inspite of the large RMSE. Indicating that there can be a tradeoff between SNR and RMSE. With a lower RMSE and higher SNR and PSNR, the graph showed that modified Wiener has a better performance than Wiener algorithm. Fig5.ps to fig7.ps represents the graph of RMSE, SNR and PSNR respectively against variance for the restoration of Scanned degraded image using Wiener and Modified Wiener. The results revealed exhibition of similar characteristics to real images with real images giving higher absolute value than the scanned images.

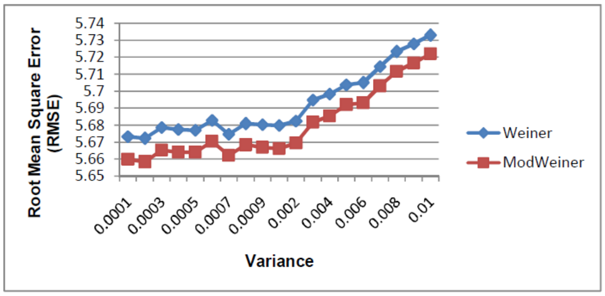



**Fig.2.** RMSE against Variance for Real degraded image with Gaussian Noise

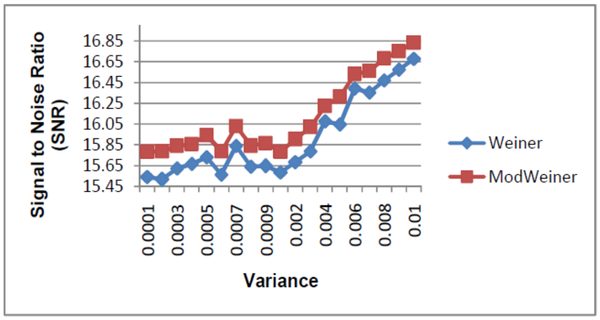



**Fig.3.** SNR against Variance for Real degraded image with Gaussian Noise

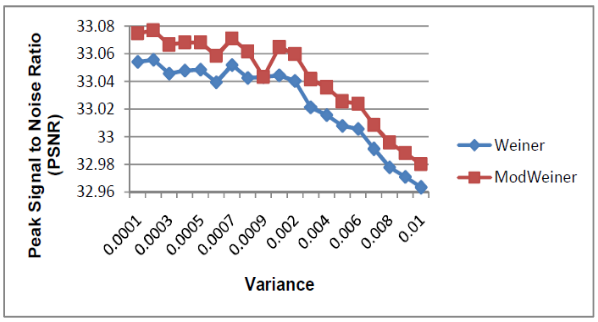



**Fig.4.** PSNR against Variance for Real degraded image with Gaussian Noise

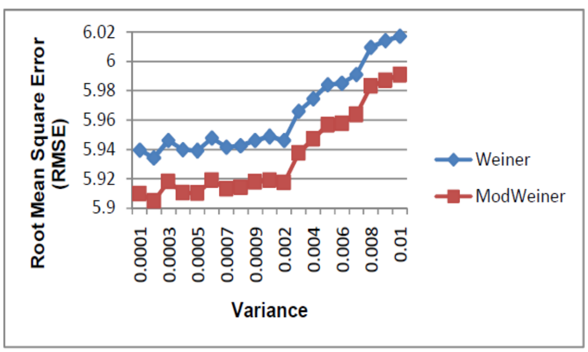



**Fig.5.** RMSE against Variance for Scanned degraded image with Gaussian Noise

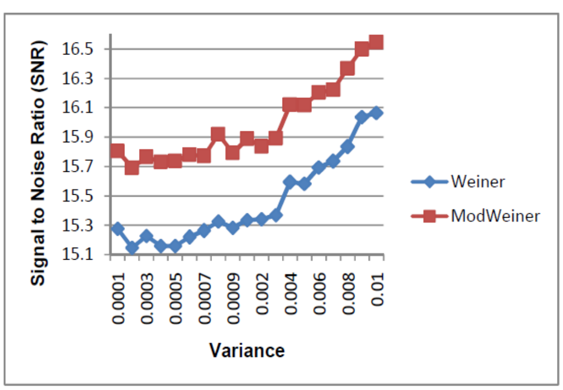



**Fig.6.** SNR against Variance for Scanned degraded image With Gaussian Noise

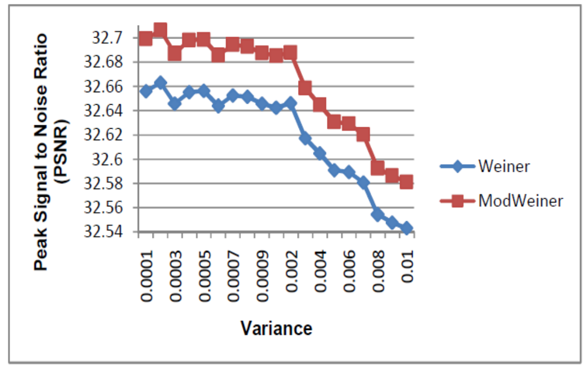


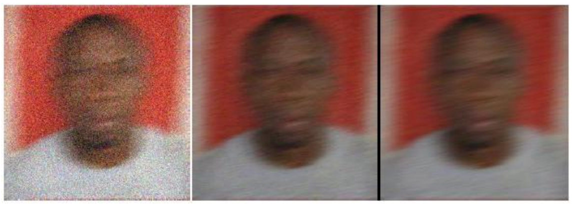

**Fig.7.** PSNR against Variance for Scanned degraded image with Gaussian Noise

Plates 1 and 2 show selected pictorial view of the results of real and scanned Image respectively. Each shows the real and scanned, blurred Noisy image, Wiener algorithm and Modified Wiener algorithms implementation respectively. Modified Wiener algorithm gave a better picture quality than Wiener for all the variance values shown. The significant change is not so much visible, this is because the differential change can only be measured by the system through the statistical measurements which has already been given by the fig2.ps to fig7.ps above.

(a) Real, Noisy blurred with Var = 0.0001, (b) Wiener algorithm (c) Modified Wiener algorithm

(a) Real, Noisy blurred with Var = 0.0002, (b) Wiener algorithm (c) Modified Wiener algorithm

(a) Real, Noisy blurred with Var = 0.008, (b) Wiener algorithm (c) Modified Wiener algorithm



(a) Real, Noisy blurred with Var = 0.01, (b) Wiener algorithm (c) Modified Wiener algorithm

Plate 1. Pictorial analysis of the algorithms using real image

(a) Scanned, Noisy blurred with Var = 0.0001, (b) Wiener algorithm (c) Modified Wiener algorithm

(a) Scanned, Noisy blurred with Var = 0.0002, (b) Wiener algorithm (c) Modified Wiener algorithm

(a) Scanned, Noisy blurred with Var = 0.008, (b) Wiener algorithm (c) Modified Wiener algorithm

(a) Scanned, Noisy blurred with Var = 0.01, (b) Wiener algorithm (c) Modified Wiener algorithm

Plate 2. Pictorial analysis of the algorithms using Scanned image.

Table 1 evaluates the overall performance of restoration for both Real and Scanned image samples between Wiener and Modified Wiener, showing that Modified Wiener is better. Modified Wiener is more efficient than Wiener with the variance values classified as low (0.0001 - 0.0009) and high (0.001 - 0.01) for all the parameters considered.

**Table1.** Summary of Results of Better Restoration between Wiener and Modified Wiener for Real and Scanned images

| Noise | Variance | RMSE | SNR | PSNR |
|---|---|---|---|---|
| Gaussian | Low | Modified Wiener | Modified Wiener | Modified Wiener |
| | High | Modified Wiener | Modified Wiener | Modified Wiener |

## 6. CONCLUSION

In this work, the developed algorithm was obtained by hybridized Constrained least error method and parametric restoration algorithm for the reconstruction of images degraded by Gaussian noise and linear motion blur. This is in order to remove the artifact which is common with Wiener restoration technique and improve signal quality. Samples of images from two imaging systems: parallel and serial acquisitions were considered. The degradation was simulated employing the linear motion blur and Gaussian noise models. The modified Wiener algorithm was applied to restore each degraded image. The performance of this algorithm was evaluated using quantitative performance measures of RMSE, SNR and PSNR with a range of noise variance, as well as in terms of visual quality of the images. The noise variance was tested for values 0.0001 to 0.01 and greater values than 0.01 in steps of 0.05 to 1.0. A similar trend of the given result ensued but literature has a stable variance value of 0.0001, that accounted for the choice range of 0.0001 to 0.01. Using RMSE and SNR as the objective measurements, the least error value and highest SNR value were found to be at variance values 0.0002 and 0.01 respectively. There arises a tradeoff between the RMSE and SNR since the values do not coincide. This means that if signal is the focus, it will be at the expense of the error. The performance was evaluated with standard Wiener algorithm. Computational results showed that modified Wiener algorithm performed optimally well in the restoration of the degraded images for both low and high noise variance values. Furthermore, the results showed that quality of the restored image from parallel acquisition was better with lower values of RMSE and higher values of SNR than the serial acquisition. The main reason for this could be attributed to the acquisition method employed.

## ACKNOWLEDGEMENTS

I would like to express my profound gratitude to all who have contributed to this work especially Engr. Prof. E. O. Omidiora and Engr. Dr. O. A. Fakolujo who painstaking supervised this work. I also appreciate Prof. J. O. Emuoyibofarhe and Dr. (Mrs.) A. B. Adetunji, for their assistance in the preparation of the manuscript.

## REFERENCES


[1] Bracewell, R. (1986). The Fourier Transform and Its Applications (2nd ed.), McGraw– Hill, New York.

[2] Brigo, D., Hanzon, B., François L. (1998). A Differential Geome- tric approach to nonlinear filtering: the Projection Filter, IEEE Transactions on Automatic Control. 43 (2): 247--252.

[3] Chang S.G., Bin Y., Vetterli M. (2006). Adaptive wavelet thres-holding for image denoising and compression, IEEE Trans. On Image Processing, 9 (9): 1532-1546.

[4] Chung-Hao C., *et al* (2008). Surveillance Systems with Automa-tic Restoration of Linear Motion and Out-of-focus Blurred Images. ICIC Express Letters. 2(4): 409-414.

[5] Del Negro (1996). Application of the Weiner filter to Magnetic Profiling in the Volcanic Environment of Mt. Etna (Italy), Annali Di Geofiscia, XXXIX(1): 67-79.

[6] Faugeras, O. D. (1983). Fundamentals in Computer Vision: Press Syndicate of the University of Cambridge, USA.

[7] Geoff D. (2009). Digital Image Processing for Medical Applica-tions, Cambridge University Press, New Delhi, India.

[8] Gonzalez R. C., Woods R. E., Eddins, S. L. (2004). Digital Image Processing Using MATLAB, 2nd edition, Gatesmark Publishing, Knoxville.

[9] Gonzalez R. C., Woods R. E. (2007). Digital Image Processing, 3rd edition, Pearson Prentice Hall.

[10] Gunn, P. J. (1975). Applications of Wiener filters to remove Au tocorrelated Noise from Magnetic Fields, Bulletin of the Aus-tralian Society of Exploration Geophysicists 5(4): 127-130.

[11] Hunt, B.R. (1973). The Application of Constrained Least Square Estimation to Image Restoration by Digital Computer, IEEE Transactions on Computers, 2: 805-812.

[12] Hykes D, *et al* (1985). Ultrasound Physics and Instrumentation, Churchill, Livingstone Inc., New York.

[13] Ju L., *et al* (2003): "Super-Resolution Image Restoration by Combining Incremental Wiener Filter and Space-Adaptive Re-gularization, IEEE International Conference Neural Networks & Signal Processing, 998-1001.

[14] Katsaggelos, A. K. (1991). Digital Image Restoration, Springer Verlag, New York.

[15] Kenneth R. C. (1996). Digital Image Processing: Prentice-Hall Inc., New Jersey.

[16] Lagendijk, R., Biemond, J. (1991). Iterative Identification and Restoration of Images, Kluwer Academy Publishers, Boston, M.A.

[17] Lagendijk R., Jan B. (1999). Basic Methods for Image Restora- tion and Identification" in Handbook of Image and Video Processing, ed. Al Bovik. New York.

[18] Ling G., Rahab K. W. (1990). Restoration of Stochastically blurred images by the Geometrical Mean Filter, Optical Engineering, 29(4): 289-295.

[19] Liu, J. J. (1997). Applications of Wiener Filtering in Image and Video De-noising, ECE497KJ Course project, 1-15.

[20] Mitchell, K. W., Gilmore, R. S. (1991): "A true Wiener Filter Im plementation for Improving Signal to Noise and Resolution in Acoustic Images', Proceedings of the 18th Annual Review, Brunswick, ME, 11A: 895-902.

[21] Pratt, W. K. (2007). Digital Image Processing, 2nd edition, Wi ley, New York.

[22] Rafael, C. G., Richard, E. W., Steven, L. E. (2003). Digital Image Processing Using MATLAB, Prentice Hall Publication, New Jersey.

[23] Ram M. N., Sudhir K. P., Stephen E. R. (2001). Effects of Uncor related and Correlated Noise on Image Information Content", Geoscience and Remote Sensing Symposium, IGARSS, IEEE 2001, 4: 1898-1900

[24] Scott E. U. ( 1998). Computer Vision and Image Processing, Prentice Hall PTR, New Jersey,

[25] Smith, J. O. (2007). Introduction to Digital Filters with audio Application, Center for Computer Research in Music and Acoustics (CCRMA), Stanford University.

[26] Thangavel, K., Manavalan, I., Aroquiaraj, I. L. (2009). Removal of Speckle Noise from Ultrasound Medical Image based on Special Filters: Comparative Study. ICGST-GVIP Journal,9, (III).


**Oke A. O.,** has B.Tech (Hons) Computer Engineering, (1998), M.Tech Computer Science, (2005), Ph.D Computer Science, (2012); Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria. Working in the same institution, 2001 till date; 31 paper publications in Journals, conference proceedings and as books.research interest includes: Image processing algorithms, Compression algorithms and hardware design and implementation. She is a Registered Engineer, The Council for Regulation of Engineering in Nigeria (COREN) and member Computer Professional (Registration) Council of Nigerian (MCPN).

**Omidiora E. O.,** has B.Sc Computer Engineering, (1991), Obafemi Awolowo University, Ile-Ife, Nigeria (1991), M.Sc Computer Science (1998), University of Lagos, Ph.D Computer Science, (2006), Ladoke Akintola University of Technology, Ogbomoso, Nigeria. A Professor of Computer Engineering, working in Ladoke Akintola University of Technology, Ogbomoso, Nigeria. Presently, he is the Head of Depart of Computer Engineering, Federal University, Oye-Ekiti, Nigeria, where he is spending his sabbatical leave. He has over 90 publications in reputable Journals and conferences. His research interest include:the study of Biometric systems and Biometric-based Algorithms and its applications to Security issues in systems, Computations Complexity measures and soft computing. He is a member of Computer Professional (Registration) Council of Nigerian (MCPN), a Registered Engineer, Council for Regulation of Engineering in Nigeria (COREN) and Corporate member, Nigerian Society of Engineers.

**Fakolujo O. A.** has a B.Sc. from Obafemi Awolowo University and a Ph. D. in Electronic/Electrical Engineering from Imperial College, UK. His research interest is in the areas Biometrics and Image Analysis and Digital Signal and Control Systems. He has published in several reputable journals and attended both many local and international conferences. He is a member of the following professional bodies: Registered Engineer, Council for Regulation of Engineering in Nigeria (COREN) and Corporate member, Nigerian Society of Engineers, Also he is a member of the Institute of Electronic and Electrical Engineering, UK.