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Impact & Analysis of WFDWT Filter on TEM Images

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Abstract
TEM images are rapidly gaining prominence in various sectors like life sciences, pathology, medical science, semiconductors, forensics, etc. Hence, there is a critical need to know the effect of existing image restoration and enhancement techniques available for TEM images. This paper focuses on WFDWT Filter. The simulation is carried on greyscale and colored TEM images separately. To do so different types of noise (Gaussian Noise, Salt & Pepper Noise, Salt & Pepper Noise & Poisson Noise) is incorporated into image. Each degraded image is denoised by filters. The result is analyzed on the basis of four parameters namely mean of the image, mean square error, signal to noise ratio, peak signal to noise ratio respectively. This paper also notices the effect on TEM image with changing parameters of the filter.

Keywords
TEM Image, Filter, Noise, Denoising

I. Introduction
TEM (Transmission Electron Microscopy) is an important morphological characterization tool for Nano-materials. Quite often a microscopy image gets corrupted by noise, which may arise in the process of acquiring the image, or during its transmission, or even during reproduction of the image. Removal of noise from an image is one of the most important tasks in image processing. Denoising techniques aim at reducing the statistical perturbations and recovering as well as possible the true underlying signal. Depending on the nature of the noise, such as additive or multiplicative type of noise, there are several approaches towards removing noise from an image. Image De-noising improves the quality of images acquired by optical, electro-optical or electronic microscopy.

Filtering techniques are used as preface action before segmentation and classification. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non redundant and unique representation of the signal [3]. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. Crudely, it states that the wavelet transform yields a large number of small coefficients and a small number of large coefficients.

Simple de-noising algorithms that use the wavelet transform consist of three steps.

- Calculate the wavelet transform of the noisy signal.
- Modify the noisy wavelet coefficients according to some rule.
- Compute the inverse transform using the modified coefficients.

One of the most well-known rules for the second step is soft thresholding. Statistical filter like Weiner filter adopted filtering in the spectral domain, but the classical Wiener filter is not adequate while it is designed primarily for additive noise suppression [3].

In this filter, the main goal was to efficiently suppress the undesirable noise level and successfully detect the fault echo that is hidden under the noise level. The dual filtering algorithm, presented in this filter, is based on application of efficient denoising algorithms as Wiener filter and discrete wavelet transform [4].

II. WFDWT Filter
It makes use of two level DWT. In first level DWT , a single level two dimensional wavelet decomposition and does soft thresholding by using mask filter for high frequency subband. At second level of DWT, it again do soft thresholding by further doing the single level two dimensional decomposition of on the approximation coefficient obtained in first level decomposition. It use wiener filter .i.e uses low pass filters a image that has been degraded by a constant power additive noise. It makes use of pixelwise adaptive wiener method based on the statistics estimated from a local neighborhood of each pixel. It then applies inverse 2D wavelet transform for second level decomposition. Then, applies the same for the first level decomposition. It De-noises image using Wiener filter for Low frequency domain and using new equation as a soft-thresholding for de-noise high-frequencies domains [5].

This filter takes five things as input parameters namely, an input image Im, name of the wavelet family wname, mask filter used for low frequency sub-band MASKL, mask filter used for high frequency sub-band MASKH, factor >=0.001, used to decrease or increase estimated power of a noise used by wiener filter. Firstly, it computes the number of layers Layer_C, for the number of layers, it performs the following steps: it applies I level discrete wavelet transform on the input image, then II level DWT transform of the first coefficient obtained in first level transformation. Thereafter, applies soft thresholding on horizontal, vertical & diagonal approximation coefficients obtained in first level DWT. It then applies soft thresholding on horizontal, vertical and diagonal approximation coefficients obtained in second level DWT. Then maximum additive noise power is computed before applying filter. It then applies wiener filter. After applying filtering process, inverse discrete wavelet transform is applied for second level. It then checks number of columns. Thereafter inverse discrete wavelet transform is applied for first level [6].

III. Noise in Microscopy Image
Noise is defined as an unwanted component of the image. Noise occurs in images for many reasons. Noise can generally be grouped into two classes, independent noise & the noise which is dependent on the image data.

A. Gaussian Noise
Gaussian noise is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution. The zero mean property of the distribution allows such noise to be removed by locally averaging pixel values [1]. Noise is modelled as additive white Gaussian noise (AWGN), where all the image pixels deviate from their original values following the Gaussian curve. That is, for each image pixel with intensity value Oij ($1 \le i \le M$, $1 \le j \le N$ for an M x N image), the corresponding pixel of the noisy image Xij is given by,

$$X_{ij}=O_{ij}+G_{ij} \tag{1}$$

where, each noise value G is drawn from a zero –mean Gaussian distribution. Gaussian noise can be reduced using a spatial filter. However, it must be kept in mind that when smoothing an image, we reduce not only the noise, but also the fine-scaled image details because they also correspond to blocked high frequencies.

B. Poisson Noise

Poisson noise, is a basic form of uncertainty associated with the measurement of light, inherent to the quantized nature of light and the independence of photon detections. Its expected magnitude is signal-dependent and constitutes the dominant source of image noise except in low-light conditions. The magnitude of poisson noise varies across the image, as it depends on the image intensity.

C. Salt & Pepper Noise

Another common form of noise is data drop-out noise (commonly referred to as intensity spikes, speckle or salt and pepper noise). Here, the noise is caused by errors in the data transmission. The corrupted pixels are either set to the maximum value (which looks like snow in the image) or have single bits flipped over. In some cases, single pixels are set alternatively to zero or to the maximum value, giving the image a `salt and pepper' like appearance. Unaffected pixels always remain unchanged. The noise is usually quantified by the percentage of pixels which are corrupted [2].

D. Speckle Noise

Increase in power of signal and noise introduced in the image is of same amount that is why speckle noise is termed as multiplicative noise [13]. It is signal dependent, non-Gaussian & spatially dependent. Due to microscopic variations in the surface, roughness within one pixel, the received signal is subjected to random variations in phase and amplitude. The variations in phase which are added constructively results in strong intensities while other which are added destructively results in low intensities. This variation is called as Speckle [1].

IV. Working Methodology

The complete simulation is carried in Matlab. Two original microscopic images, one greyscale and one colour, are taken. Noise is added to the original image. Four types of noises are added namely gaussian noise, speckle noise, salt & pepper noise & poisson noise respectively. This distorted image is then filtered using WFDWT filter algorithm and is also analyzed with changing parameters as shown in fig. 2.

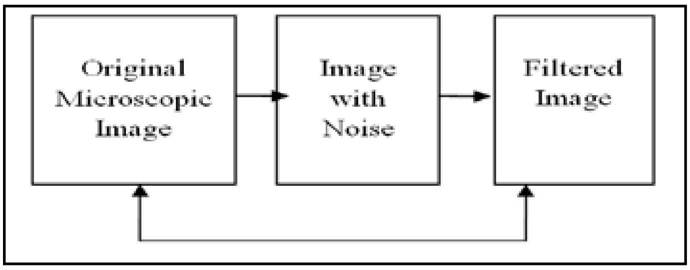

Fig. 1: Working Methodology

V. Implementation of WFDWT Filter on TEM Images

Implementation is carried for each colored and greyscale TEM image.

A. For colored TEM Image

1. With Change in wname

wname indicates name of the wavelet family. The figures 2.1 to 2.4 shows how the mean, mse, snr and psnr ratios of the filtered image changes as the wavelet family changes for each of the degraded image with gaussian, speckle , salt and pepper and poisson noises respectively.

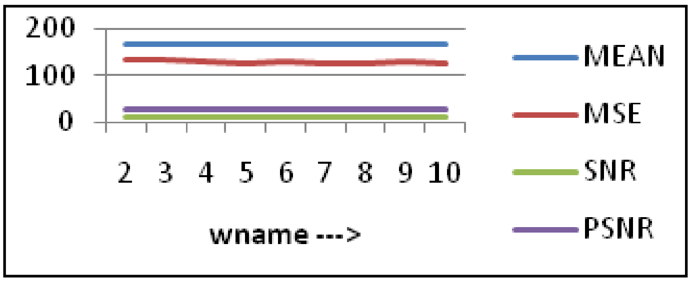

Fig. 2.1 Gaussian Noise

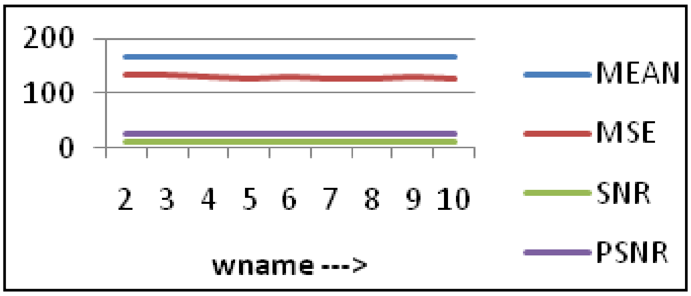

Fig. 2.2 Speckle Noise

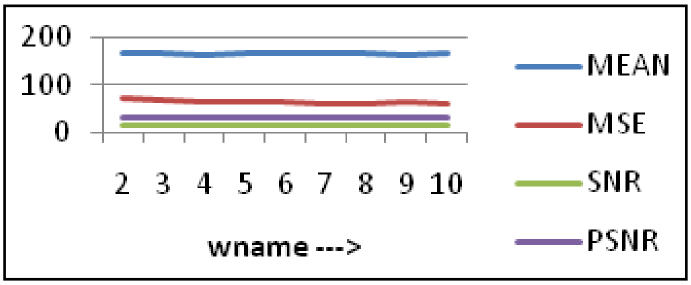

Fig. 2.3 Salt & Pepper Noise

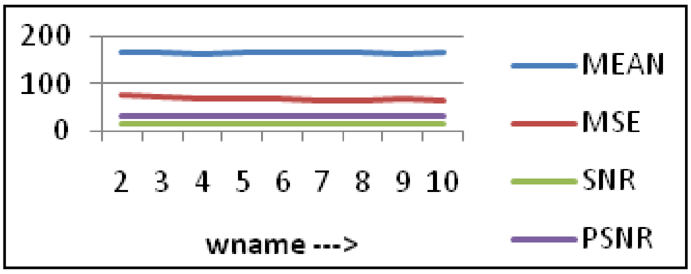

Fig. 2.4 Poisson Noise

With wavelet family db9, mean of the filtered image is found to be minimum and with wavelet family db8, minimum mse and highest snr and psnr ratios are obtained each type of noise.

2. With Change in MASKL

MASKL is the mask filter used for low frequency subband.. It can be [3 3], [5 5], [7 7].The figures 3.1 to 3.4 shows how the mean, mse, snr and psnr ratios of the filtered image changes as the window size changes for each of the degraded image with gaussian, speckle , salt and pepper and poisson noises respectively. Image is denoised using wiener filter for low frequency domain.

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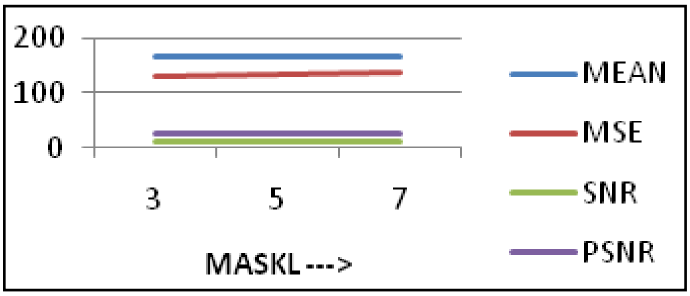

Fig. 3.1 Gaussian Noise

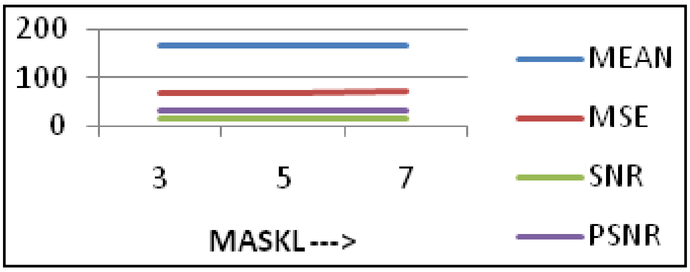

Fig. 3.2 Speckle Noise

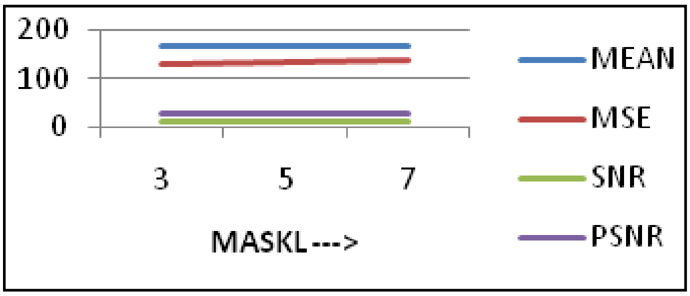

Fig. 3.3 Salt & Pepper Noise

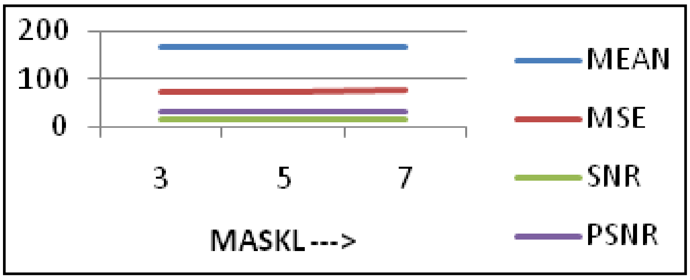

Fig. 3.4 Poisson Noise

It is observed that with the increasing size of the window mean, snr and psnr ratios of the filtered image are decreasing while mse is found to be increasing for each type of noise. Thus, for the smallest window size [3 3] , with the least mean square error, highest snr and psnr ratios are obtained while we get the minimum mean of the filtered image as we move down with increased window size.

3. With Changing MASKH

MASKH is the mask filter for high frequency subband. The figures 4.1 to 4.4 shows how the mean mse, snr and psnr ratios of the filtered image changes as the window size changes for each of the degraded image with gaussian, speckle, salt and pepper and poisson noise respectively. For high frequency domain soft thresholding is done.

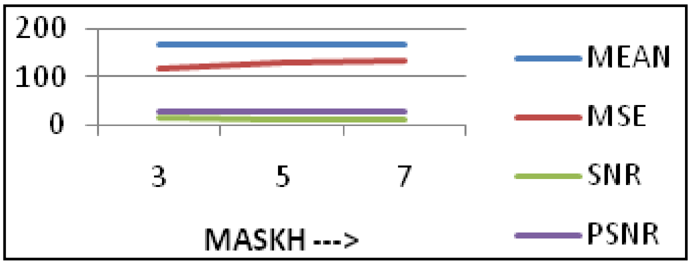

Fig. 4.1 Gaussian Noise

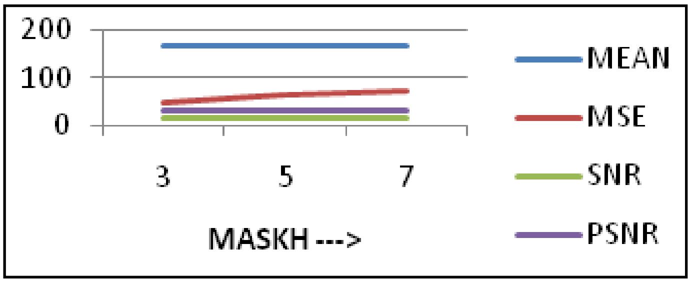

Fig. 4.2 Speckle Noise

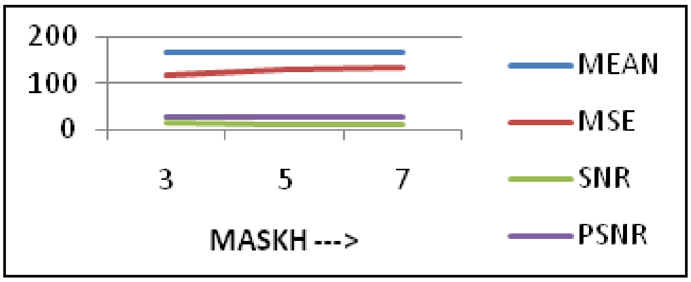

Fig. 4.3 Salt & Pepper Noise

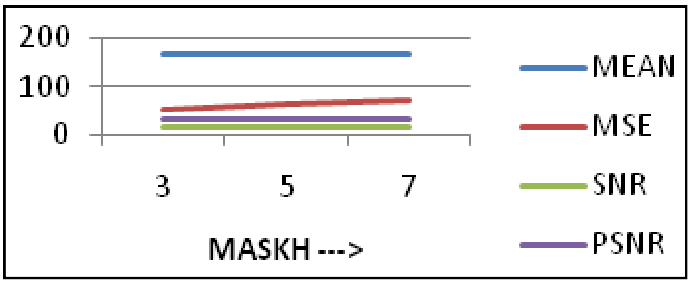

Fig. 4. 4 Poisson Noise

It is seen that with the increasing size of the window mean, snr and psnr ratios of the filtered image are decreasing while mse is found to be increasing for each type of noise. Thus, for the smallest window size [3 3] , with the least mean square error, highest snr and psnr ratios are obtained while we get the minimum mean of the filtered image as we move down with increased window size.

4. With Changing Factor

This parameter is >=0.001, this parameter is used to decrease or increase Estimated power of a Noise used by the Wiener Filter. Figures 5.1 to 5.4 indicate that how the mean, mse, snr and psnr ratios of the filtered image vary with varying parameter.

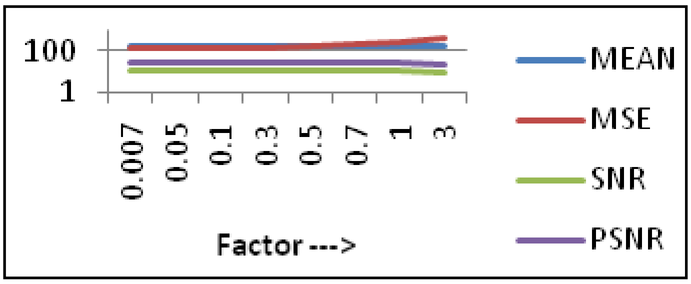

Fig. 5.1 Gaussian Noise

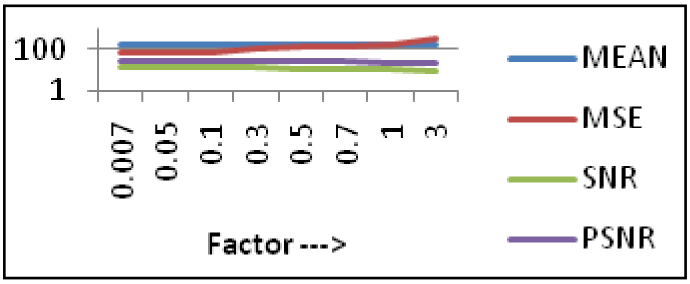

Fig. 5.2 Speckle Noise

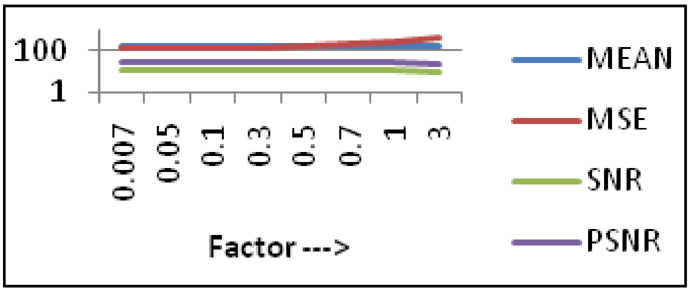

Fig. 5.3 Salt & Pepper Noise

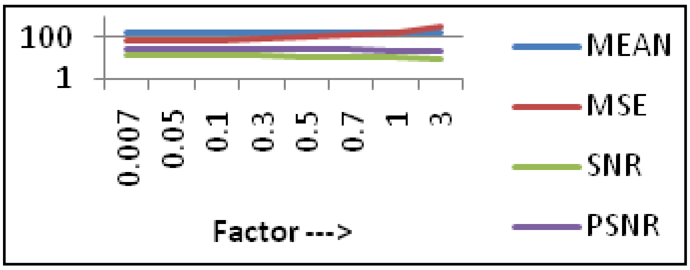

Fig. 5.4 Poisson Noise

It is observed that for gaussian and salt & pepper noise factor=0.3 is giving the optimum result as with minimum mse highest snr and psnr ratios are obtained whereas foe speckle and poisson noise different pattern is observed that we are getting desirable result with the minimum quite low values of factor.

B. For Greyscale TEM Image

1. With Change in wname

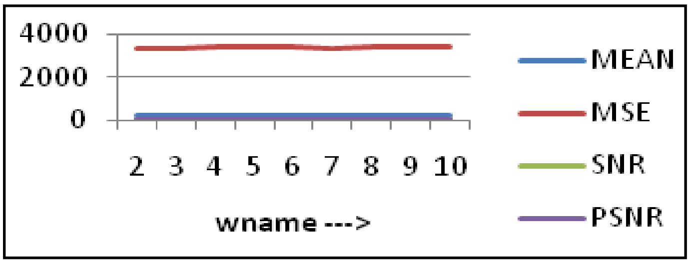

Fig. 6.1 Gaussian Noise

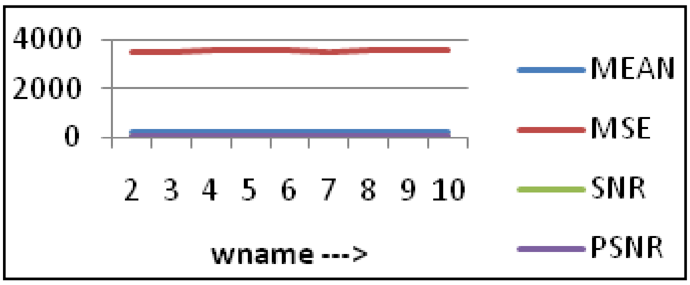

Fig. 6.2 Speckle Noise

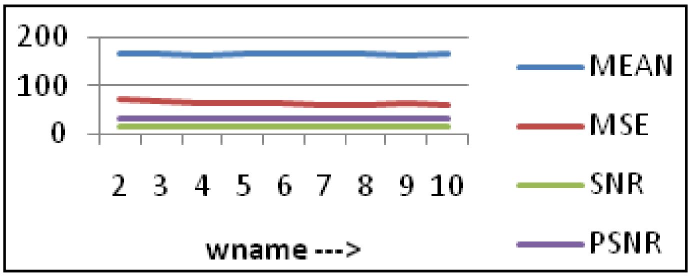

Fig. 6.3 Salt & Pepper Noise

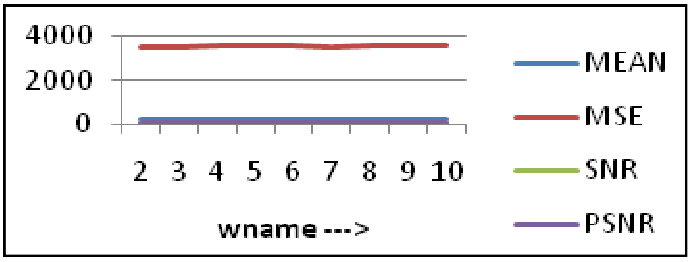

Fig. 6.4 Poisson Noise

For db2 family a desirable statistics are observed, with minimum mse, higher snr and psnr ratios are obtained while minimum mean is seen for db9 family for each type of noise.

2. With change in MASKL

For every type of noise, as the mask size or the size of window is increased, the optimum results are\obtained, with lowest mean and mse, highest snr and psnr ratios are obtained.

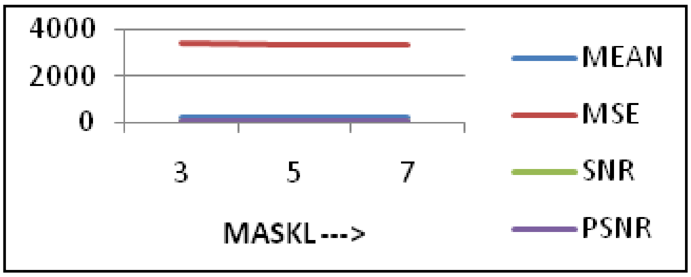

Fig. 7.1 Gaussian Noise

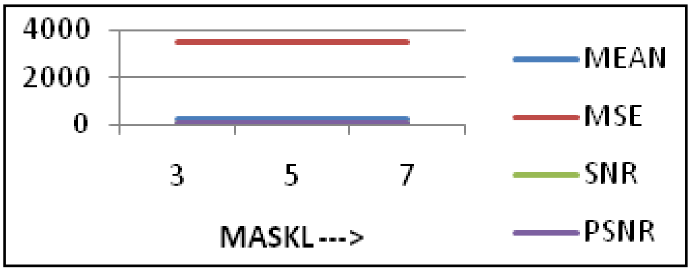

Fig. 7.2 Speckle Noise

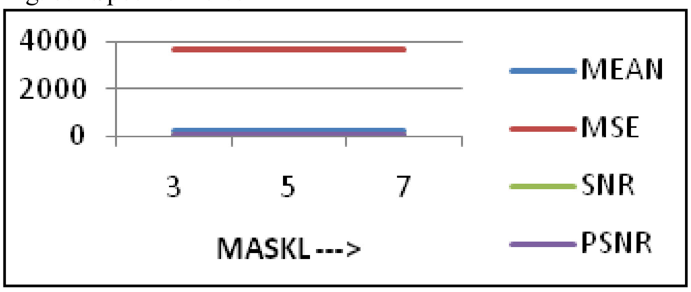

Fig. 7.3 Salt & Pepper Noise

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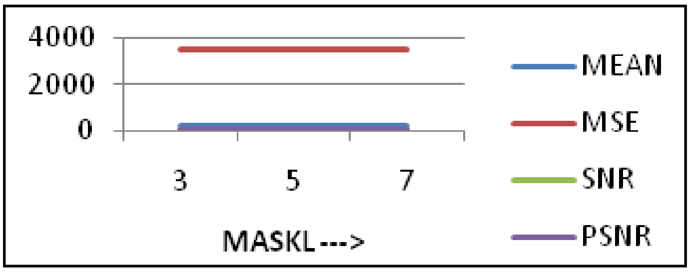


Fig. 7.4 Poisson Noise

3. With Changing MASKH

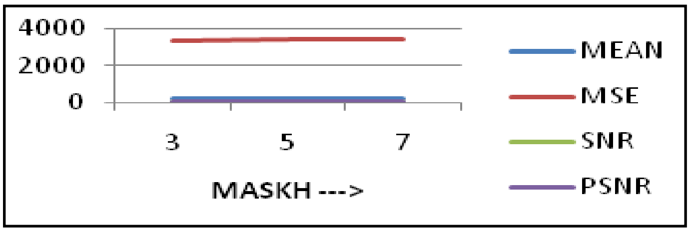


Fig. 8.1 Gaussian Noise

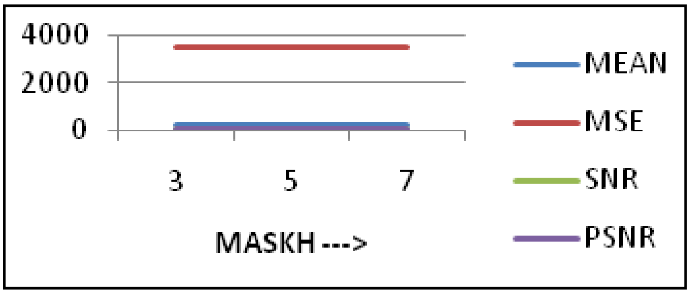


Fig. 8.2 Speckle Noise

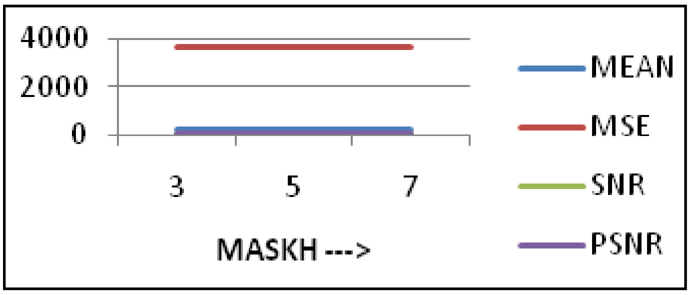


Fig. 8.3 Salt & Pepper Noise

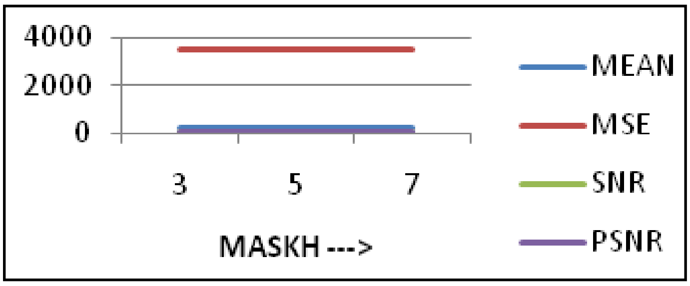


Fig. 8.4 Poisson Noise

Here, we get the minimum mse with the highest snr and psnr ratios for the smallest window size=3 while the minimum mean value of the filtered image as we increase the window size.

4. With Changing Factor

It is found that as we increase the factor results obtained are very desirable, we get minimum mean, minimum mse, and higher snr and psnr ratios.

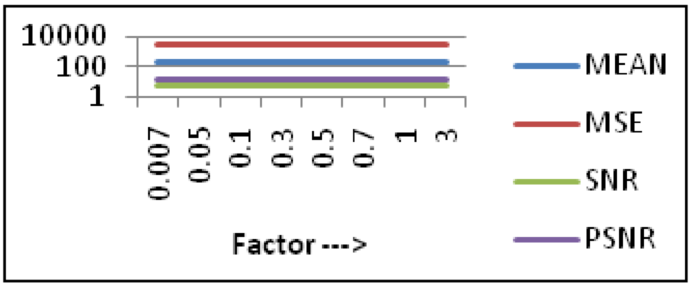


Fig. 9.1 Gaussian Noise

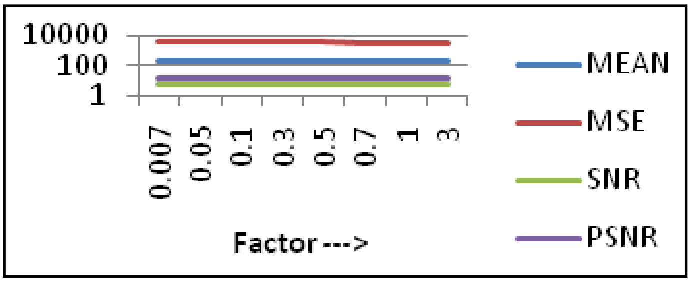


Fig. 9.2 Speckle Noise

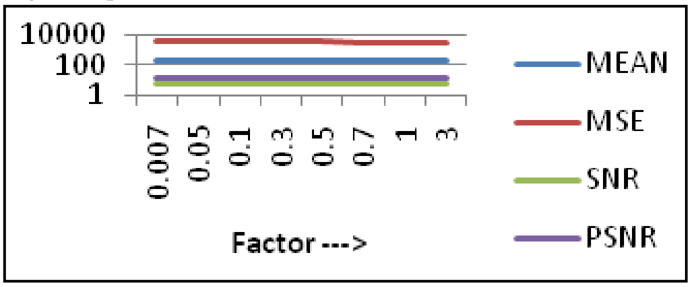


Fig. 9.3 Salt & Pepper Noise

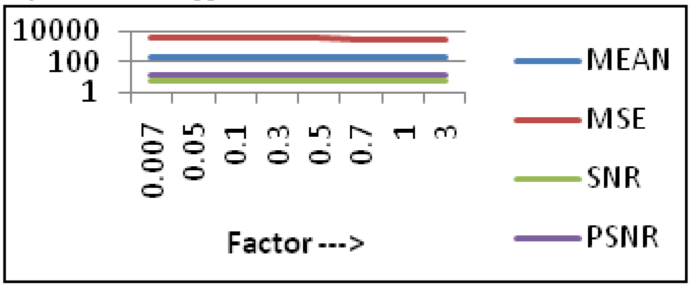


Fig. 9.4 Poisson Noise

IV. Conclusion

Simulations when carried out in MATLAB for degraded image with varying noise and intensity levels, it is seen that WFDWT filter gives best result for Speckle noise for both colored and greyscale TEM image. Also, db8 wavelet family, small kernel size for low frequency and higher frequency subbands, factor=0.1 found to give better results for colored TEM image.db2 wavelet family, higher kernel size for low frequency subband, small kernel size for high frequency subband & higher values of factor are desirable in case of greyscale TEM image

VII. Simulation Results

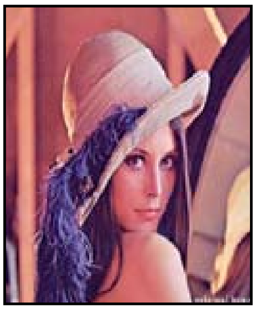
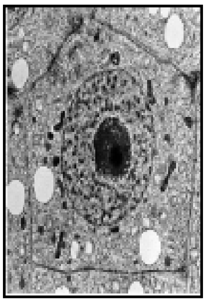
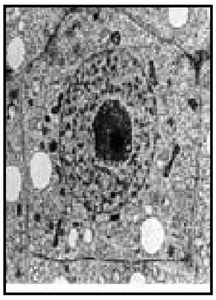
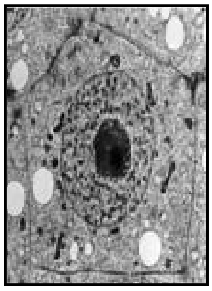
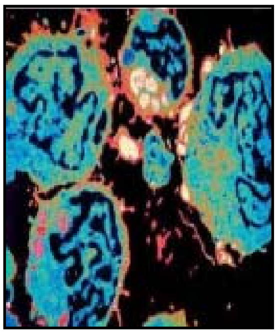
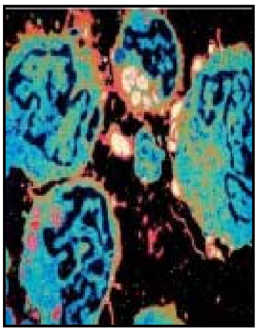
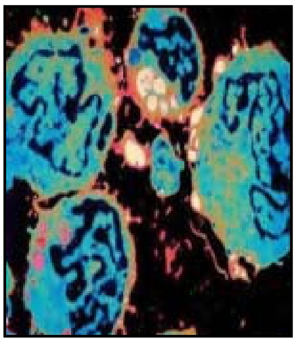
WIENER FILTER USING DWT			
	Original Image	Noisy Image	Filtered Image
Greyscale Normal Image			
Colored Normal Image			
Greyscale TEM Image			
Colored TEM Image			

Fig. 10: Simulation Results

VIII. Future Scope

An algorithm can be further modified for noises other than gaussian too. Also edges are found to be blurred which can be improved by further modification to the algorithm.

References

[1] Charles Boncelet,"Image Noise Models", In Alan C. Bovik. Handbook of Image and Video Processing. Academic Press, 2005.

[2] Rafael C. Gonzalez, Richard E. Woods,"Digital Image Processing", Pearson Prentice Hall, 2007.

[3] S.Sudha, G.R.Suresh, R.Sukaneshspeckle,"Noise Reduction In Ultrasound Images By Wavelet Thresholding Based On Weighted Variance", International Journal Of Computer Theory & Engineering, Vol. 1, No. 1, April 2009 1793-8201.

[4] Hiroko Furuya, Shintaro Eda, Testuya Shimamura,"Image Restoration Via Wiener Filtering", In The Frequency

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Domainwseas Transactions on Signal Processing.

[5] Václav MATZ, Marcel KREIDL, Radislav ŠMID, Stanislav ŠTARMAN,"Ultrasonic Signal De-noising Using Dual Filtering Algorithm17th World Conference on Nondestructive Testing", 25-28 Oct 2008, Shanghai, China.

[6] S.Kother Mohideen, Dr. S. Arumuga Perumal, Dr. M. Mohamed Sathik,"Image De-noising using Discrete Wavelet transform", IJCSNS International Journal of Computer Science and Network Security, Vol. 8, No. 1, January 2008.