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Comparison of Denoising Filters on Greyscale TEM Image for Different Noise

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Abstract: *TEM (Transmission Electron Microscopy) are currently the most widely used techniques to study nanoparticles morphology. Removal of noise from an image is one of the most important tasks in image processing. 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. This paper compares five filters on the measures of mean of image, signal to noise ratio, peak signal to noise ratio & mean square error. In this work four types of noise (Gaussian noise, Salt & Pepper noise, Speckle noise and Poisson noise) is used and image de-noising performed for different noise. Further results have been compared for all noises. . In this paper four types of noise are used and image de-noising performed for different noise by various filters (WFDWT, BF, HMDF, FDE, and DVROFT). Further results have been compared for all noises. It is observed that for Gaussian Noise WFDWT & for other noises HMDF has shown the better performance results.*
Keyword: *Nonmaterial, Noise, Denoising, Filters, Quality*

I. Introduction

Image denoising can be considered as a component of processing or as a process itself. Image denoising involves the manipulation of the image data to produce a visually high quality image. Images get often corrupted by additive and multiplicative noise. In today's real time applications and requirements resolution we get from normal images is not sufficient. We need look insight its crystallographic structure, topography, morphology etc of a substance. As nanoscopic image has got wide and significant use in the medical research and applications and in many other domains. Due to acquisition TEM images contain electronic noise and white diffraction artifacts localized on the edges of the Nanomaterials Various types of filters have been proposed for removal of noise in these microscopic images. This paper discusses the major types of noise used in simulation in the first part, few types of filters being simulated on a nanoscopic image in the second part and comparative analysis in the third part.

II. Noise In An Microscopic Image

We define noise as an unwanted component of the image. Noise occurs in images for many reasons. Image is the sum of the true pixel value and a random Gaussian distributed noise value. As the name indicates, this type of noise has a Gaussian distribution, which has a bell shaped probability distribution function.

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. This makes removing such noise very difficult.

Salt and pepper noise is an impulse type of noise, which is also referred to as intensity spikes. This is caused generally due to errors in data transmission. It has only two possible values, *a* and *b*. The probability of each is typically less than 0.1. The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. [2]

Speckle noise is a multiplicative noise. 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]

III. Denoising Filters

A. Bilateral Filter

Bilateral filtering is a non-linear filtering technique. It extends the concept of Gaussian smoothing by weighting the filter coefficients with their corresponding relative pixel intensities. Pixels that are very different in intensity from the central pixel are weighted less even though they may be in close proximity to the central pixel. This is effectively a convolution with a non-linear Gaussian filter, with weights based on pixel intensities. This is applied as two Gaussian filters at a localized pixel neighbourhood, one in the spatial domain, named the domain filter, and one in the intensity domain, named the range filter. Bilateral filter compares the intensity of the pixel to be filtered with the surrounding filtered intensities instead of the noisy ones. [3].

$$\tilde{I}(\mathbf{x}) = \frac{1}{C} \sum_{y \in N(x)} e^{\frac{-\|\mathbf{y}-\mathbf{x}\|^2}{2\sigma_d^2}} \, e^{\frac{-|I(\mathbf{y})-I(\mathbf{x})|^2}{2\sigma_r^2}} \, I(y)$$

Fig.1 Bilateral Filter Equation

B. Weiner Filter using DWT

Wiener filter minimizes the mean square error between the uncorrupted signal and the estimated signal. Discrete Wavelet Transform analyzes the signal by successive use of low pass and high pass filtering to decompose the signal into its coarse and detail information. This denoising algorithm de-noise image using Wiener filter for Low frequency domain and using soft thresholding for de-noise High-frequencies domains. This approach is gives better results than (DWT or Wiener) de-noising. [4,8]

C. Hybrid Median Filter

Median filter is widely used in digital image processing for removing noise in digital images. Although it does not shift edges, the median filter does remove fine lines and detail, and round corners. A more advanced version of this filter, which avoids these problems, is the hybrid median. Hybrid median filtering preserves edges better than a NxN square kernel-based median filter because data from different spatial directions are ranked separately. Three median values are calculated in the NxN box: MR is the median of horizontal and vertical R pixels, and MD is the median of diagonal D pixels. The filtered value is the median of the two median values and the central pixel C: median ([MR, MD, C]). [5]

$$\begin{bmatrix} D & * & R & * & D \\ * & D & R & D & * \\ R & R & DCR & R & R \\ * & D & R & D & * \\ D & * & R & * & D \end{bmatrix}$$

Fig. 3 Formulation of Filtered Value

D. Dual Vectorial ROF Filter

Regularity is of central importance in computer vision. Total variation preserves edges and does not requires any prior information about the blurred image computed. One approach is to replace norm $l2$ in Tikhonov Regularization with the norm $l1$, i.e., the 1-norm of the first spatial derivation of the solution. This is called the total variation (TV) regularization. This method will help to obtain the discontinuities or steep gradients in the restored image. This procedure minimizes the vectorial total variation norm.[6] Let us consider a vectorial (or M-dimensional or multichannel) function u, such as a color image or a vector field, defined on a bounded open domain $\Omega \subset R^N$ as $x \rightarrow u(x) := (u1(x), ..., u_M(x))$, $u : \rightarrow R^M$,

$$\inf_{\mathbf{u}} \sup_{|\mathbf{p}| \leq 1} \left\{ < \mathbf{u}, \nabla \cdot \mathbf{p} >_{L^2(\Omega;\mathbb{R}^M)} + \frac{1}{2\lambda} \|\mathbf{f} - \mathbf{u}\|^2_{L^2(\Omega;\mathbb{R}^M)} \right\}$$

Fig. 2 Formulation of Vectorial TV Norm

Which is convex in u and concave in p and the set {|p|<=1} is bounded and convex.[11,12]

E. Fuzzy Histogram Equalization

It proposes a novel modification of the brightness preserving dynamic histogram equalization technique to improve its brightness preserving and contrast enhancement abilities while reducing its computational complexity. This technique, called uses fuzzy statistics of digital images for their representation and processing. Representation and processing of images in the fuzzy domain enables the technique to handle the inexactness of gray level values in a better way, resulting in improved performance. Besides, the imprecision in gray levels is handled well by fuzzy statistics, fuzzy histogram, when computed with appropriate fuzzy membership function, does not have random fluctuations or missing intensity levels and is essentially smooth. This helps in obtaining its meaningful partitioning required for brightness preserving equalization.[7]

IV. Simulation Results

The four types of noise are added to the original image ranging from 1% to 9% and are filtered with the above mentioned filters. The filtered image is compared with the original image on the basis of four characteristics shown in the Fig. 4.1 to 4.16

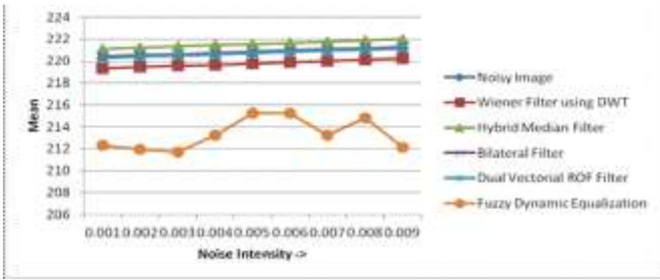

Fig. 4.1 Mean of Image after applying various filters on Gaussian Noise corrupted image.

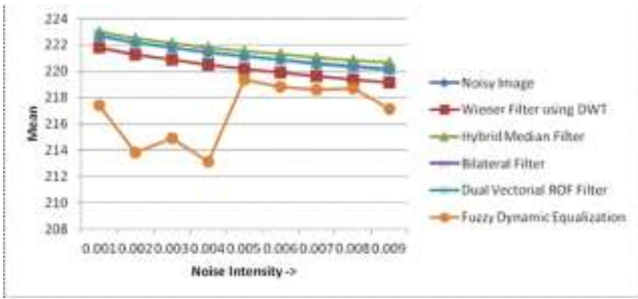

Fig.4.2 Mean of Image after applying various filters on Speckle Noise corrupted image

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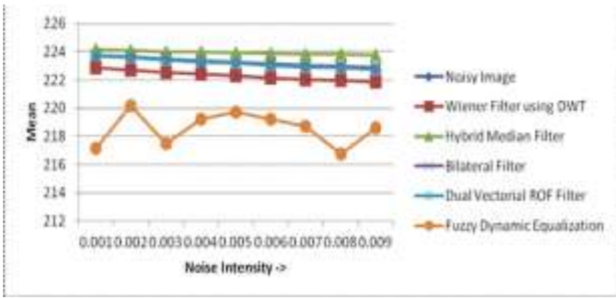

Fig.4.3 Mean of Image after applying various filters on Salt & Pepper Noise corrupted image.

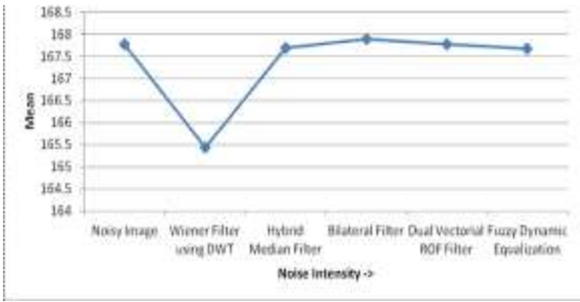

Fig.4.4 Mean of Image after applying various filters on Salt & Pepper Noise corrupted image.

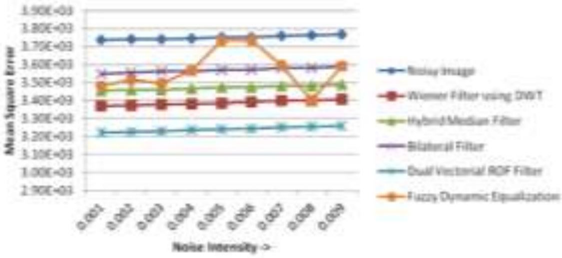

Fig.4.5 Mean Square Error of Image after applying various filters on Gaussian Noise corrupted image.

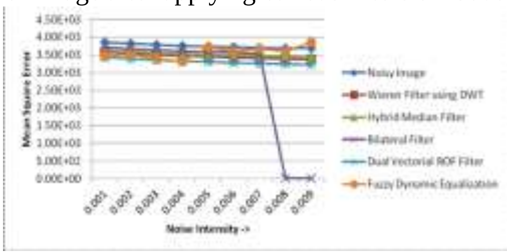

Fig.4.6 Mean Square Error of Image after applying various filters on Speckle Noise corrupted image.

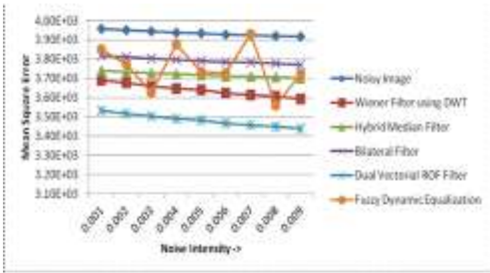

Fig.4.7 Mean Square Error of Image after applying various filters on Salt & Pepper Noise corrupted image.

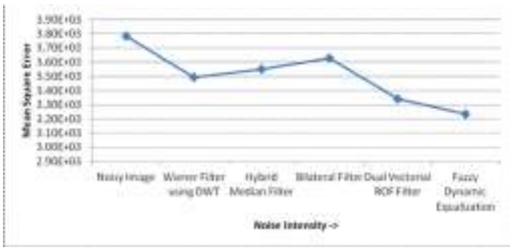

Fig.4.8 Mean Square Error of Image after applying various filters on Poisson Noise corrupted image.

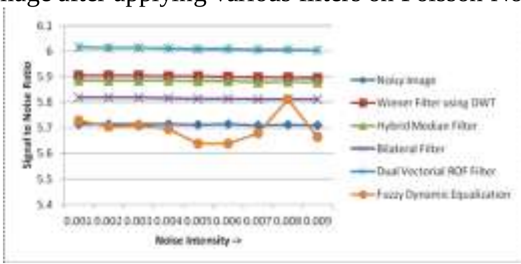

Fig.4.9 Signal to Noise Ratio of Image after applying various filters on Gaussian Noise corrupted image.

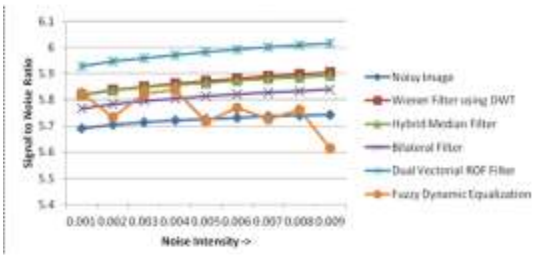

Fig.4.10 Signal to Noise Ratio of Image after applying various filters on Speckle Noise corrupted image.

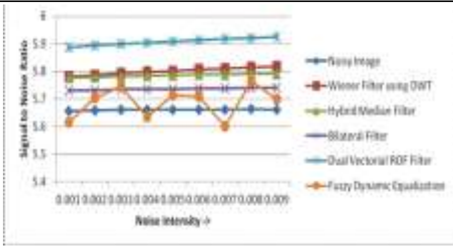

Fig.4.11 Signal to Noise Ratio of Image after applying various filters on Salt & Pepper Noise corrupted image.

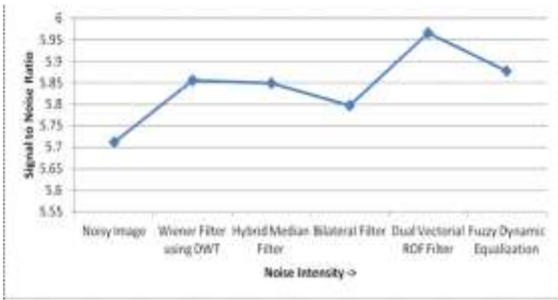

Fig.4.12 Signal to Noise Ratio of Image after applying various filters on Poisson Noise corrupted image.

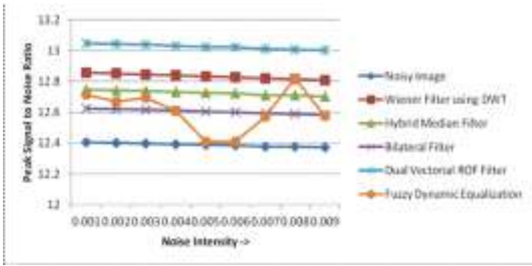

Fig.4.13 Peak Signal to Noise Ratio of Image after applying various filters on Gaussian Noise corrupted image.

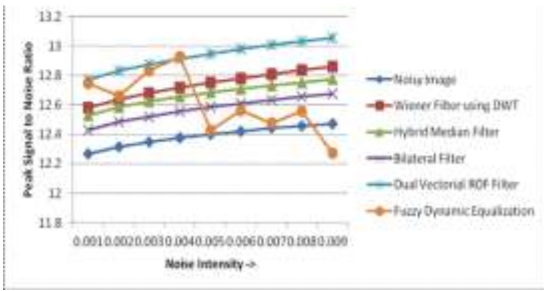

Fig.4.14 Peak Signal to Noise Ratio of Image after applying various filters on Speckle Noise corrupted image.

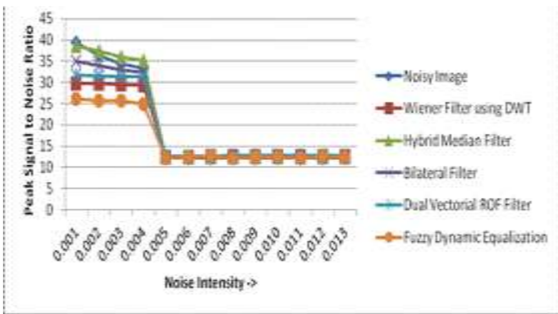

Fig.4.15 Peak Signal to Noise Ratio of Image after applying various filters on Salt & Pepper Noise corrupted image.

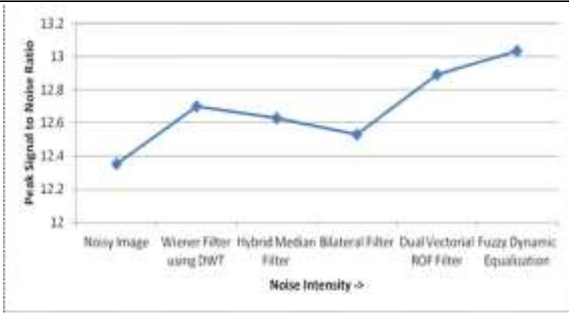

Fig.4.16 Peak Signal to Noise Ratio of Image after applying various filters on Poisson Noise corrupted image.

TABLE 5.1
AVERAGE MEAN VALUES OF FILTERED IMAGES

MEAN RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	220.7368	221.2334	223.2045	221.621
Wiener Filter using DWT	**219.7848**	220.2959	222.3188	220.6939
Hybrid Median Filter	221.5626	221.6444	223.9298	222.0618
Bilateral Filter	220.8592	221.2602	223.2843	221.6503
Dual Vectorial ROF Filter	220.7411	221.2407	223.2132	221.6225
Fuzzy Dynamic Equalization	213.3209	**216.8765**	**218.5587**	**212.6344**

TABLE 5.2
AVERAGE MEAN SQUARE ERROR VALUES OF THE FILTERED IMAGES

MEAN SQUARE ERROR RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	3751.6888	3752.044	3935.5444	3785
Wiener Filter using DWT	3387.1556	3461.322	3638.4333	3494.3
Hybrid Median Filter	3471.3111	3516	3719.0556	3549.8
Bilateral Filter	3569.8725	**2815.593**	3793.125	3628.395
Dual Vectorial ROF Filter	**3240.2333**	3309.378	**3482**	3341.1
Fuzzy Dynamic Equalization	3568.9444	3570.233	3756.7667	**3234**

TABLE 5.3
AVERAGE SIGNAL TO NOISE RATIO VALUES OF FILTERED IMAGE

SIGNAL TO NOISE RATIO RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	5.7130	5.7238	5.6606	5.7126
Wiener Filter using DWT	5.9004	5.8682	5.8015	5.8555
Hybrid Median Filter	5.8827	5.8612	5.7853	5.8485
Bilateral Filter	5.8154	5.8096	5.7362	5.7966
Dual Vectorial ROF Filter	**6.0099**	**5.9784**	**5.9083**	**5.9651**
Fuzzy Dynamic Equalization	5.6967	5.7566	5.6875	5.8774

TABLE 5.4
AVERAGE PEAK SIGNAL TO NOISE RATIO VALUES OF FILTERED IMAGES

PEAK SIGNAL TO NOISE RATIO RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	12.3885	12.3886	12.1807	12.3502
Wiener Filter using DWT	12.8324	12.7392	12.5218	12.6972
Hybrid Median Filter	12.7258	12.671	12.4265	12.6287
Bilateral Filter	12.6044	12.5720	12.3410	12.53
Dual Vectorial ROF Filter	**13.0250**	**12.9342**	**12.7127**	**12.8919**
Fuzzy Dynamic Equalization	12.6073	12.6082	12.3845	13.0335

VI. Conclusion

We used the greyscale TEM Image adding four types of noise (Speckle, Gaussian, Poisson and Salt & Pepper) in original image and de-noised all noisy images by all filters. Graphs are shown in Fig 4.1 to 4.16 on the basis of four parameters (Mean, Mean Square Error, Signal to Noise Ratio & Peak Signal to Noise Ratio). The result for in each category for every filter is summarized in tables 4.1 to 4.4. The following table concludes the complete discussion made in paper.

TABLE 6.1
AN APPROPRIATE FILTER AGAINST EACH TYPE OF NOISE AND CHARACTERISTIC PAIR

	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Mean	Wiener Filter using DWT	Fuzzy Dynamic Equalization	Fuzzy Dynamic Equalization	Fuzzy Dynamic Equalization
Mean Square Error	**Dual Vectorial ROF Filter**	Bilateral Filter	**Dual Vectorial ROF Filter**	Fuzzy Dynamic Equalization
Signal to Noise Ratio	**Dual Vectorial ROF Filter**	**Dual Vectorial ROF Filter**	**Dual Vectorial ROF Filter**	**Dual Vectorial ROF Filter**
Peak Signal to Noise Ratio	**Dual Vectorial ROF Filter**	**Dual Vectorial ROF Filter**	**Dual Vectorial ROF Filter**	**Dual Vectorial ROF Filter**

From simulation results and denoised images it is found that for each kind of noise Dual Vectorial ROF Filter works better than others.

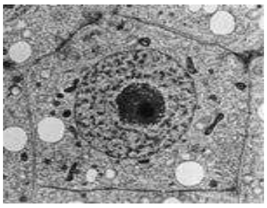

Fig. 6.1 Original Image

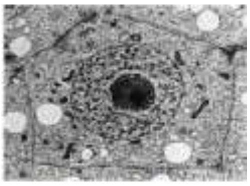

Fig. 6.2 Image with Gaussian Noise

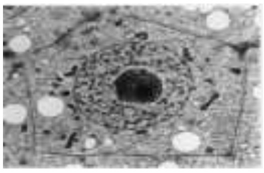

Fig. 6.3 Filtered Image of Fig.6.2 by Dual Vectorial ROF Filter.

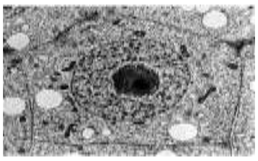

Fig. 6.4 Image with Speckle Noise 0.005

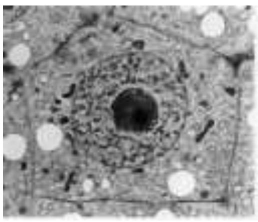

Fig. 6.5 Filtered Image of Fig.6.4 by Dual Vectorial ROF

Filter

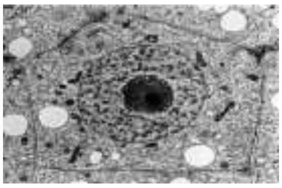

Fig. 6.6 Image with Salt & Pepper Noise 0.005

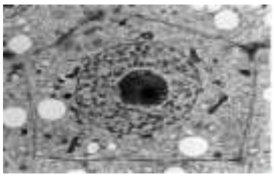

Fig. 6.7 Filtered Image of Fig.6.6 by Dual Vectorial ROF Filter.

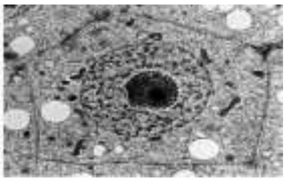

Fig. 6.8 Image with Poisson Noise 0.005

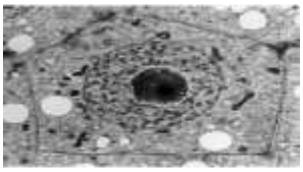

Fig. 6.9 Filtered Image of Fig.6.8 by Dual Vectorial ROF Filter.

VI. Future Scope

Though Dual Vectorial ROF Filters retains the structure in the image but do not capture very fine details due to smoothing. Further these algorithms can be modified to overcome the drawbacks.

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