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COMPARISON OF DENOISING FILTERS ON COLOUR TEM IMAGE FOR DIFFERENT NOISE

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Abstract— 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. 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 paper four types of noise (Gaussian noise, Salt & Pepper noise, Speckle noise and Poisson noise) is used and image de-noising performed for different noise by various filters (WFDWT, BF, HMDF, FDE, 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.

Keywords— *Nanomaterials, Noise, Denoising, Filters, Qualit.*

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[1]. 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. Filtering is the most popular method to reduce noise. In the spatial domain, filtering depends on location and its neighbours. In the frequency domain, filtering multiplies the whole image and the mask. Some filters operate in spatial domain, some filters are mathematically derived from frequency domain to spatial domain, other filters are designed for special noise, combination of two or more filters, or derivation from other filters [2, 8]. An early and very popular approach was to achieve filtering in the frequency domain, just by trimming high-frequency components of the image spectrum. The Wiener filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring. Wiener filters are often applied in the frequency domain Wiener filters are unable to reconstruct frequency components which have been degraded by noise. This computationally fast method has however a major drawback: it tends to smooth out the salient features of the signal, such as edges and textures [4]. Wavelets and other transformations in a combined space-frequency domain nicely address this issue and lead to very efficient filtering schemes. In wavelet thresholding, a signal is decomposed into its approximation (low-frequency) and detail (high-frequency) sub-bands; since most of the image information is concentrated in a few large coefficients, the detail s sub-bands are processed with hard or soft thresholding operations[9,10,11]. This methodology constitutes an important achievement in the field of the edge preserving denoising algorithms, suitable to deal with the discontinuities associated with anatomical details. The median filter provides a mechanism for reducing image noise, while preserving edges more effectively than a linear smoothing filter [5]. Many common image-processing techniques such as rank-order and morphological processing are variations on the basic median algorithm, and the filter can be used as a steppingstone to more sophisticated effects. However, due to existing algorithms' fundamental slowness, its practical use has typically been restricted to small kernel sizes and/or low-resolution images [3, 13].Traditional filtering is domain filtering, and enforces closeness by weighing pixel values with coefficients that fall off with distance. Similarly, we define range filtering, which averages image values with weights that decay with dissimilarity. Range filters are nonlinear because their weights depend on image intensity or color. Bilateral Filter is the combination of both domain and range filters. Total variation denoising (TV) is a special case of image regularization methods that balances a smoothness measure and a fidelity term [6, 12]. This paper discusses the major types of noises, various types of filters applied on a nanoscopic image. It discusses the performance of each filter on a nanoscopic image by making comparisons on the basis of certain image quality metrics like mean , mean square error, signal to noise ratio & peak signal to noise ratio.

II. NOISE IN AN MICROSCOPIC IMAGE

We define noise 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. Additive noise is evenly distributed over the frequency domain (i.e. white noise), whereas an image contains mostly low frequency information. Hence, the noise is dominant for high frequencies and its effects can be reduced using some kind of lowpass filter. This can be done either with a frequency filter or with a spatial filter. (Often a spatial filter is preferable, as it is computationally less expensive than a frequency filter.)In the second case of data-dependent noise (e.g. arising when monochromatic radiation is scattered from a surface whose roughness is of the order of a wavelength, causing wave interference which results in image speckle), it is possible to model noise with a multiplicative, or non-linear, model. These models are mathematically more complicated; hence, if possible, the noise is assumed to be data independent.

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 O_{ij} ($1 \leq i \leq M$, $1 \leq j \leq N$ for an M x N image), the corresponding pixel of the noisy image X_{ij} is given by,

Xij=Oij+Gij (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]

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 swith 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]

Mathematically, at a pixel location x, the output of bilateral filter is calculated as shown in Fig.1

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

Fig.1 Bilateral Filter Equation

where sigmad and sigma r are parameters controlling fall-off of weights in spatial and intensity domains respectively, N (x) is a spatial neighbourhood of pixel I (x), and C is the normalization constant. Bilateral Filter is not parameter free. The set of bilateral filter parameters has an important influence on its performance and behaviour.

B. Weiner Filter using DWT

Wiener filter minimizes the mean square error between the uncorrupted signal and the estimated signal. The inverse filtering is a restoration technique for deconvolution, i.e., when the image is blurred by a known lowpass filter, it is possible to recover the image by inverse filtering or generalized inverse filtering. The orthogonality principle implies that the Wiener filter in Fourier domain can be expressed as

$$W(f_1, f_2) = \frac{H^*(f_1, f_2) S_{xx}(f_1, f_2)}{|H(f_1, f_2)|^2 S_{xx}(f_1, f_2) + S_{\eta\eta}(f_1, f_2)},$$

where $S_{xx}(f_1, f_2), S_{\eta\eta}(f_1, f_2)$ are respectively power spectra of the original image and the additive noise, and H(f1,f2) is the blurring filter. 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. By taking only a limited number of highest coefficients of the discrete wavelet transform, an inverse transform (with the same wavelet basis) more or less denoised signal can be obtained. [9]It is very effective because of its ability to capture energy of signal in few energy transform values.[10] 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]

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 [13]. 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 l^1, 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] VTV minimization model is based on the dual formulation of the vectorial TV norm. 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

$x \rightarrow u(x) := (u_1(x), ..., u_M(x))$, u : $\rightarrow R^M$,

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

Fig. 4 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. METHODOLOGY USED

The complete simulation is carried in Matlab. The original microscopic image is 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 some algorithm and is compared with the statistics of original image to interpret that to what extent filter is able to denoise the image as shown in Fig.2

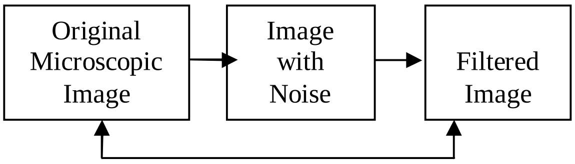

Fig. 5 Block Diagram

VI. SIMULATION RESULTS

A. Gaussian Noise

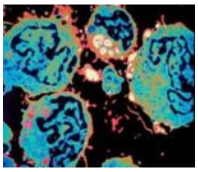
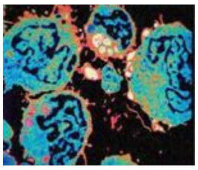

Fig.6 a Original **Fig 6b Noisy**

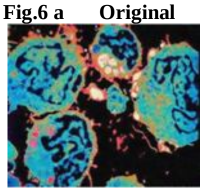
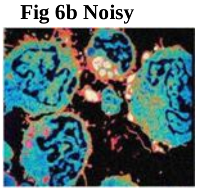

Fig 6 c WFDWT **Fig 6d HMDF**

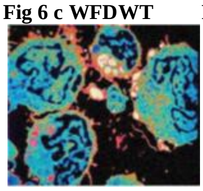
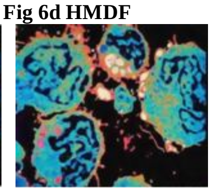

Fig 6e BF **fig 6f DVROFT**

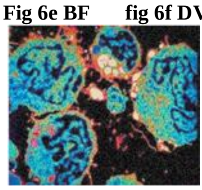

Fig 6g FDE

From fig. 6c when the image with gaussian noise is filtered using WFDWT , edges are preserved but are not sharp while when filtered using HMDFT & BF, images obtained are blurred in fig.6d & 6e , DVROFT filter preserves the edges sharply and removes the blurring effect from fig.6f.

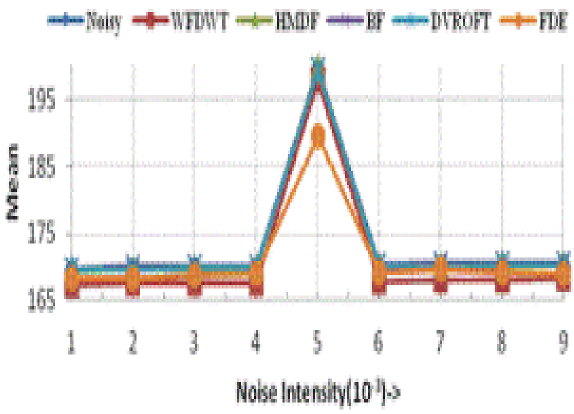

Fig. 7a Mean of Filtered Images with Gaussian Noise

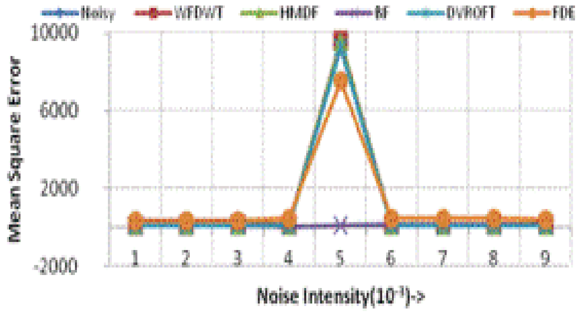

Fig. 7b MSE of Filtered Images with Gaussian Noise

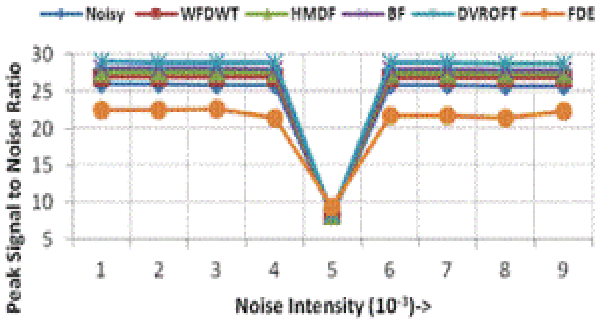

Fig. 7c PSNR of Filtered Images with Gaussian Noise

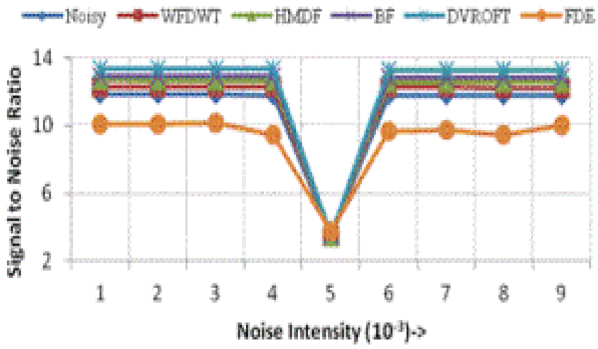

Fig. 7d SNR of Filtered Images with Gaussian Noise

When noise is introduced in the image the mean of image increased. When filtered with WFDWT, the mean is reduced significantly.The mean squared error (MSE) for our practical purposes allows us to compare the "true" pixel values of our original image to our degraded image. The MSE represents the average of the squares of the "errors" between our actual image and our noisy image. The error is the amount by which the values of the original image differ from the degraded image. Fig. 7b shows that BF gives the minimum value. Higher the SNR better is the reconstructed image, from Fig 7d, for nanoscopic image with gaussian noise , DVROFT filter gives the maximum value. Higher the PSNR, the better degraded image has been reconstructed to match the original image and the better the reconstructive algorithm. This would occur because we wish to minimize the MSE between images with respect the maximum signal value of the image. Fig. 7c depicts that BF gives the maximum value.

B. Speckle Noise

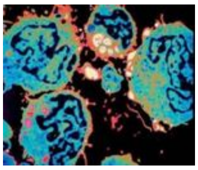
Fig 8a Original

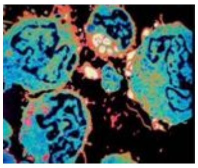
fig 8b Noisy

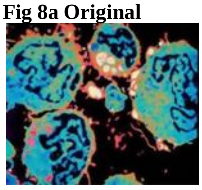
Fig 8cWFDWT

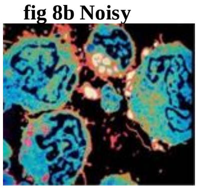
fig 8d HMDF

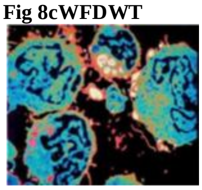
Fig 8e BF

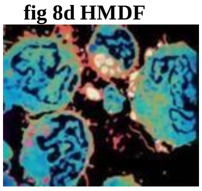
fig 8f DVROFT

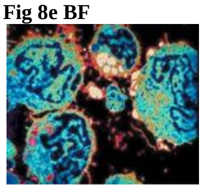
Fig 8g FDE

From fig. 8c to 8g it is clear that nanoscopic image with speckle noise is best filtered by HMDF.

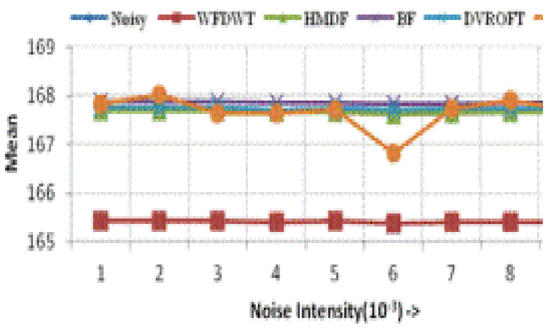

Fig. 9a MEAN of Filtered Images with Speckle Noise

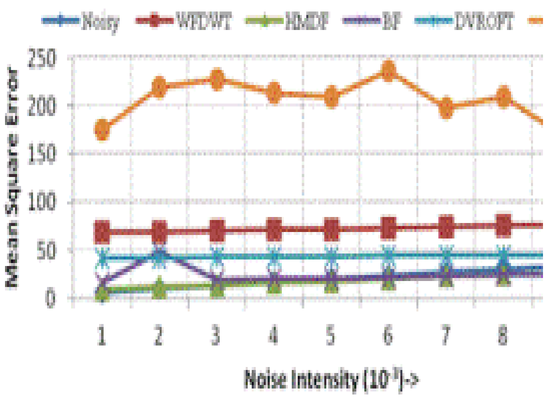

Fig. 9b MSE of Filtered Images with Speckle Noise

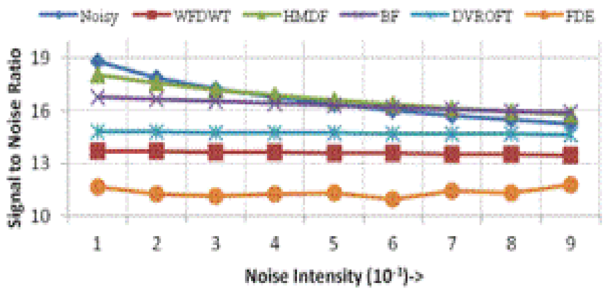

Fig. 9c SNR of Filtered Images with Gaussian Noise

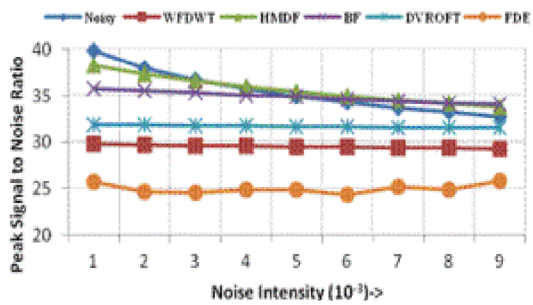

Fig. 9d PSNR of Filtered Images with Speckle Noise

Fig. 9a depicts that WFDWT gives the minimum value. Fig. 9b depicts that HMDF gives the minimum value. Fig. 9c depicts that HMDF gives the maximum value. Fig. 9d depicts that HMDF gives the maximum value.

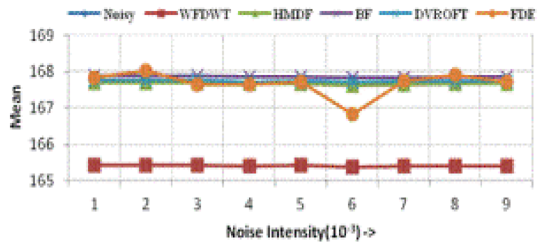

Fig. 9a MEAN of Filtered Images with Speckle Noise

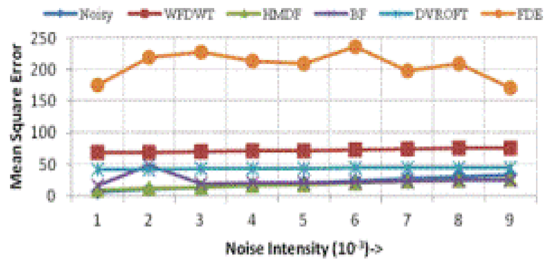

Fig. 9b MSE of Filtered Images with Speckle Noise

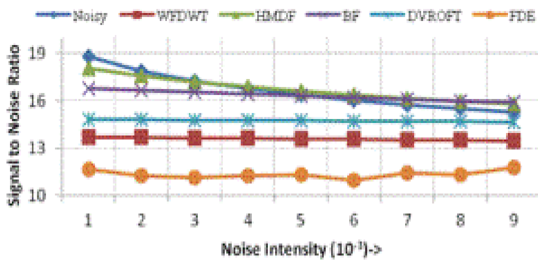

Fig. 9c SNR of Filtered Images with Gaussian Noise

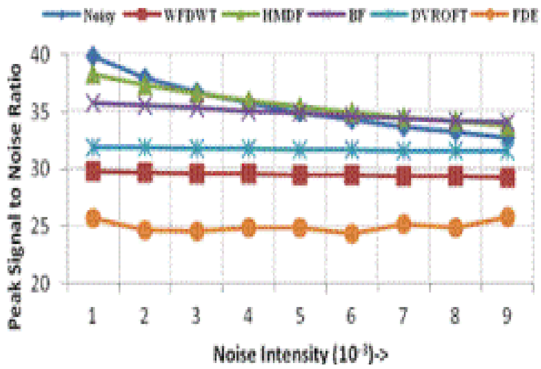

Fig. 9d PSNR of Filtered Images with Speckle Noise

Fig. 9a depicts that WFDWT gives the minimum value. Fig. 9b depicts that HMDF gives the minimum value. Fig. 9c depicts that HMDF gives the maximum value. Fig. 9d depicts that HMDF gives the maximum value.

C. Salt & Pepper Noise

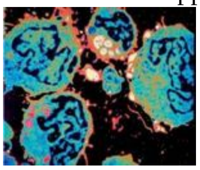

Fig 10a Original

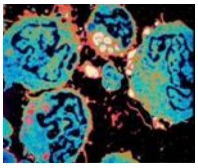

fig10b Noisy

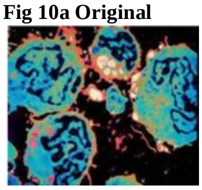

Fig 10c WFDWT

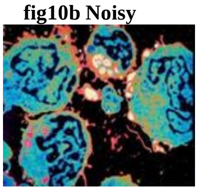

fig 10d HMDF

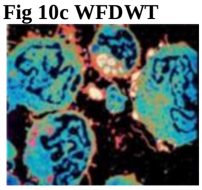

Fig 10e BF

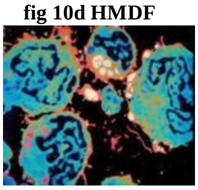

Fig 10f DVROFT

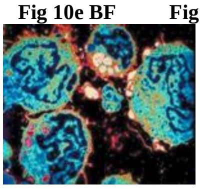

Fig 10g FDE

From fig. 10a to 10g it is clear that image with salt & pepper noise is best removed by HMDF.

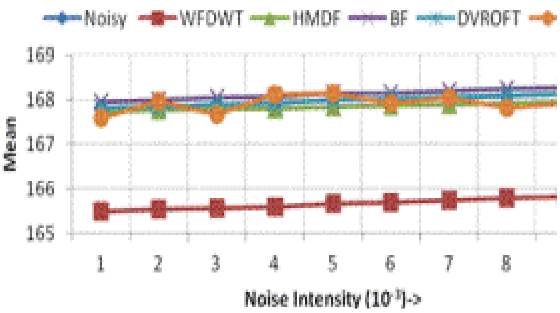

Fig. 11a MEAN of Filtered Images with Salt & Pepper Noise

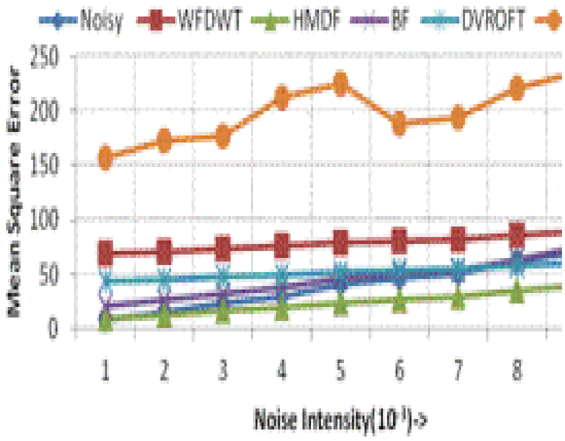

Fig. 11b MSE of Filtered Images with Salt & Pepper Noise

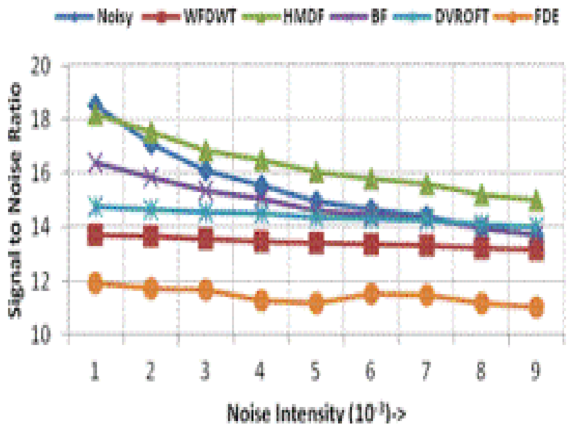

Fig 11c SNR of Filtered Images with Salt & Pepper Noise

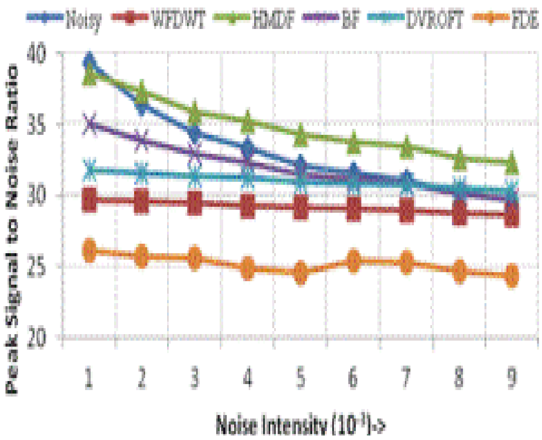

Fig. 11d PSNR of Filtered Images with Salt & Pepper Noise

Fig. 11a depicts that HMDF gives the minimum value. Fig. 11b depicts that HMDF gives the minimum value. Fig. 11c depicts that HMDF gives the maximum value. Fig. 11d depicts that HMDF gives the maximum value.

D. Poisson Noise

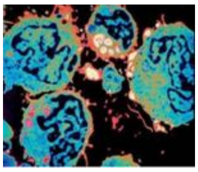

Fig 12a original

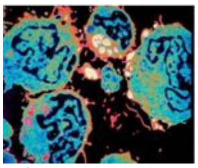

fig 12b noisy

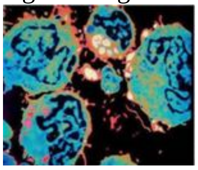

Fig 12c WFDWT

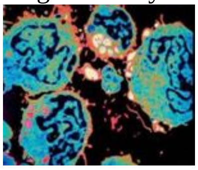

fig 12d HMDF

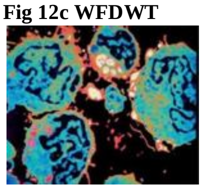

Fig 12e BF

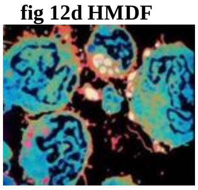

fig 12f DVROFT

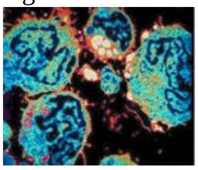

Fig 12g FDE

From fig. 12c to 12g it is clear that HMDF performs the best on nanoscopic image with poisson noise.

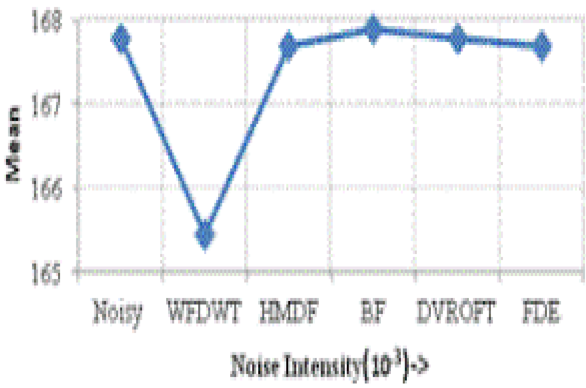

Fig. 13a Mean of Filtered Images with Poisson Noise

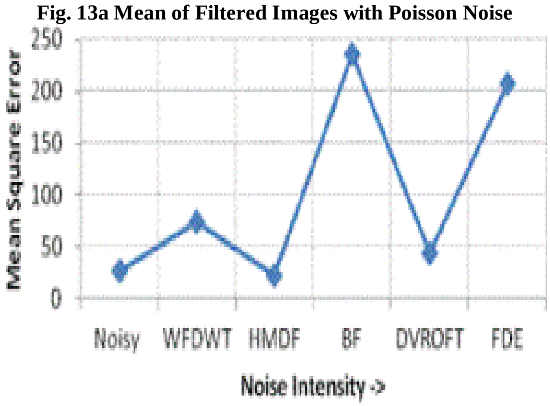

Fig. 13b MSE of Filtered Images with Poisson Noise

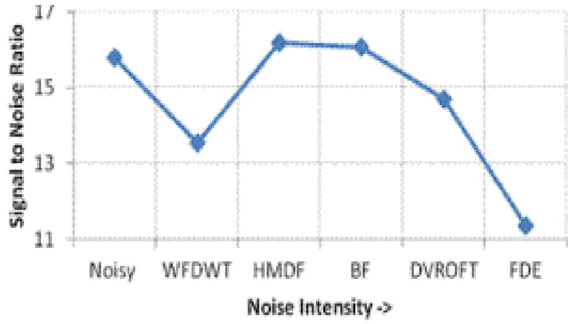

Fig 13c SNR of Filtered Images with Poisson Noise

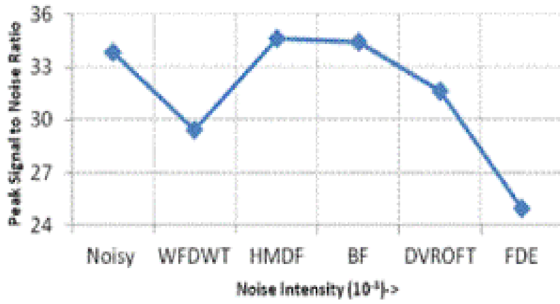

Fig. 13d PSNR of Filtered Images with Poisson Noise

From Fig.13, it is clear that WFDWT better reduces the mean value of the image while HMDF keeping the minimum MSE gives the maximum SNR & PSNR.

IV. CONCLUSION

An Image is denoised with four types of noise. For each type of noise the noise intensity variation taken is 0.001 to 0.009 i.e 1% to 9% . For each of these images four parameters Mean, MSE, SNR & PSNR are measured . Table 1 to Table 4 shows the averaged values. From Fig 6 to Fig 13, & Table 1 to Table 4 it is clear that for colour nanoscopic image with

a) Gaussian noise DVROFT filter has better performance.
b) Speckle , Salt & pepper and Poisson Noise HMDF has the better performance.

The conclusion is shown in Table 5

TABLE 5

	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
MEAN	WFDWT	WFDWT	WFDWT	WFDWT
MSE	BF	**HMDF**	**HMDF**	**HMDF**
SNR	DVROFT	**HMDF**	**HMDF**	**HMDF**
PSNR	DVROFT	**HMDF**	**HMDF**	**HMDF**

V. FUTURE SCOPE

Though Dual Vectorial ROF Filters retains the structure in the image with high SNR & PSNR as compared when implemented on normal images but there is a blurring along edges as observed from Fig.3, 7 9 & 11. Hybrid Filter de-noise the image but affects the sharpness of edges. In all the results obtained images lost the actual color along the edge due to smoothing. Further these algorithms can be modified to overcome these drawbacks.

REFERENCES

[1] Charles Boncelet (2005). "Image Noise Models". In Alan C. Bovik. Handbook of Image and Video Processing. Academic Press. ISBN 0-12-119792-1.

[2] Rafael C. Gonzalez, Richard E. Woods (2007). Digital Image Processing, Pearson Prentice Hall. ISBN 0-13-168728-X

[3] Arnaud DeDecker1, JohnA.Lee 2, MichelVerleysen A principled approach to image denoising with similarity kernels involving patches Elsevier Neurocomputing 73 (2010) 1199–1209

[4] Václav MATZ, Marcel KREIDL, Radislav ŠMID and Stanislav ŠTARMAN, Ultrasonic Signal De-noising Using Dual Filtering Algorithm, 17th World Conference on Nondestructive Testing, 25-28 Oct 2008, Shanghai, China

[5] R.Vanithamani 1, G.Umamaheswari2, M.Ezhilarasi Published in: Proceeding ICNVS'10 Proceedings of the 12th international conference on Networking, VLSI and signal processing Pages 166-171 World Scientific and Engineering Academy and Society (WSEAS) Stevens Point, Wisconsin, USA ©2010 table of contents ISBN: 978-960-474-162-5

[6] Xavier Bresson, Tony Chan, Fast dual minimization of the vectorial total variation norm and applications to color image processing, Inverse Problems & Imaging (2008) Volume: 2, Issue 4, Pages: 455-484, ISSN: 19308337, DOI: 10.3934/ipi.2008.2.455

[7] D. Sheet, H. Garud, A. Suveer, J. Chatterjee and M. Mahadevappa, "Brightness Preserving Dynamic Fuzzy Histogram Equalization", IEEE Trans., Consumer Electronics, vol. 56, no. 4, pp. 2475 - 2480, Nov. 2010

[8] A.K.Jain, Fundamentals of digital image processing, Prentice Hall, Englewood cliffs, 1989 .

[9] Kazubek, M.; Wavelet domain image denoising by thresholding and Wiener Filtering Signal Processing Letters, IEEE , Volume: 10 , Issue: 11 , Nov. 2003

[10] 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

[11] Frank Bauera, Sergei Pereverzevb, Lorenzo Rosascoc, On regularization algorithms in learning theory, Elsevier Journal of Complexity 23 (2007) 52 – 72

[12] cam 07-25, Recent UCLA Computational and Applied Mathematics Reports

[13] I. Shanthi, Dr. M.L. Valarmathi, Speckle Noise Suppression of SAR color image using Hybrid Median Filter, International Journal of Computer Applications (0975-8887), Volume-31-No-9, October 2011

TABLE 1

MEAN RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	173.24	167.74	167.98	167.77
WFDWT	**171.06**	**165.41**	**165.65**	**165.44**
HMDF	173.19	167.67	167.84	167.70
BF	173.52	167.86	168.12	167.90
DVROFT	173.25	167.74	167.98	167.77
FDE	171.13	167.68	167.91	167.68

TABLE 2

MEAN SQUARE ERROR RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	1207.38	20.68	38.19	26.70
WFDWT	1184.00	72.39	78.49	74.22
HMDF	1161.46	**18.42**	**23.45**	**22.36**
BF	**102.51**	24.73	44.97	235.62
DVROFT	1103.38	43.70	51.20	44.40
FDE	1204.36	206.62	197.95	206.85

TABLE 3

SIGNAL TO NOISE RATIO RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	10.89	16.61	15.44	15.81
WFDWT	11.29	13.59	13.42	13.53
HMDF	11.60	**16.72**	**16.30**	**16.19**
BF	11.84	16.32	14.85	16.07
DVROFT	**12.22**	14.72	14.39	14.69
FDE	9.15	11.35	11.45	11.34

TABLE 4

PEAK SIGNAL TO NOISE RATIO RESULTS	Gaussian Noise	Speckle Noise	Salt & Pepper Noise	Poisson Noise
Noisy	23.92	35.47	33.14	33.87
WFDWT	24.80	29.54	29.20	29.43
HMDF	25.34	**35.70**	**34.85**	**34.64**
BF	**25.83**	34.90	31.96	34.41
DVROFT	26.62	31.73	31.06	31.66
FDE	20.63	25.00	25.20	24.97