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PERFORMANCE ANALYSIS OF A MODIFIED DECOMPOSITION FILTER FOR NON IDENTICAL NOISES

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Abstract
The proposed work aims in the restoration of images corrupted by Gaussian noise, impulse noise. The new algorithm significantly removes different noises and produce better image quality than standard median filter (SMF), Centre weighted median filter (CWF) and threshold decomposition filter (TDF).The proposed algorithm (PA) is tested on different images corrupted by all two noises and is found to produce better results in terms of the qualitative and quantitative measures of the image for noise densities up to 30% noise level for impulse noise, mean zero and 0.9% variance of Gaussian noise. The filter works well for speckle noise up to 0.8% variance.

Keywords:
Impulse Noise, Median Filter, Threshold Decomposition, Non-linear Filter

1. INTRODUCTION

Images are often corrupted by noise, due to degradation introduced at the input channels, transmission medium, sensor and/or digitizer. Common types of degradation are blurring, distortion, additive random noise such as Gaussian white noise and salt-and-pepper impulse noise, signal-dependent noise such as speckle, film grain noise and quantization noise [2]. In order to restore back these images, a proper filter should be carefully chosen. A good noise removal filter would remove the additive noise distributions exactly, restoring the original image from the noisy image completely. To do this, the filtering algorithm must be specially designed to remove a particular noise distribution. In reality, no matter how well a noise removal filter is designed, the restored image always exhibits a certain degree of deviation in its pixel values from the original image. Excessive deviation often renders the restored image useless. In other words, the restored image may be visually unacceptable if subjected to human inspection [3]. The additive white Gaussian noise which are caused by poor image acquisition or by transferring the image data in noisy communication channels. Gaussian noise removal can be effectively done by linear filtering methods. Impulse noise is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel. Two common types of impulse noise are the salt-and-pepper noise and the random-valued noise. For images corrupted by salt-and pepper noise, the noisy pixels can take only the maximum and the minimum values while in the case of random-valued noise; they can take any random value in the dynamic range. Speckle is a random, deterministic, interference pattern in an image formed with coherent radiation of a medium containing many sub-resolution scatterers. The texture of the observed speckle pattern does not correspond to underlying structure. The local brightness of the speckle pattern, however, does reflect the local echogenicity of the underlying scatterers [3]. There are two basic approaches to image de-noising, spatial filtering methods and transform domain filtering methods [4]. A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be classified into non-linear and linear filters. Many non-linear filters fall into the category of order statistic neighbor operators [5]. This means that the local neighbors are sorted into ascending order and this list is processed to give an estimate of the underlying image brightness. The simplest order statistic operator is the median [6], where the central value in the ordered list is used for the new value of the brightness. The median is good at reducing impulse noise However, A mean or average filter is the optimal linear filter for Gaussian noise removal which tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise. This paper is organized as follows. Section II describes noise model. Section III gives a brief review of related work on Image De-noising using proposed algorithm. Section IV deals with Exhaustive Experimental Results and Discussions and finally Concluding Remarks are given in Section V.

2. NOISE MODEL

Let the true image x belong to a proper function space $S(\Omega)$ on $\Omega = [0; 1]^2$, and the observed digital image y be a vector in R^{mxm} indexed by $A = \{1,2,..m\}X\{1,2,.m\}$. The image degradation can be modeled as $y = N(Hx)$, where $H : S(\Omega) \rightarrow R^{mxm}$ is a linear operator representing blurring, and $N : R^{mxm} \rightarrow R^{mxm}$ models the noise. Usually, $y = Hx + \sigma n$ where $\sigma n \in R^{mxm}$ is an additive zero-mean Gaussian noise with standard deviation $\sigma >= 0$. Outliers are modeled as impulse noise. For an overview, see [7].

$$y' = Hx + \sigma g \tag{1}$$

$$y = N(y') \tag{2}$$

where N represents the impulse noise. There are two common models for impulse noise: the salt-and-pepper noise and the random-valued noise. If $[d\min; d\max]$ denote the dynamic range of y', i.e., $d\min <= y'_{ij} <= d\max$ for all (i,j), then they are denoted by Salt-and-pepper noise: the gray level of y at pixel location $(i\ j)$ is

$y_{ij} = d\min$; with probability p;
$d\max$; with probaility q;
y'_{ij}; with probability $1 - p - q$;

Where $s = p + q$ denotes the salt-and-pepper noise level [7].

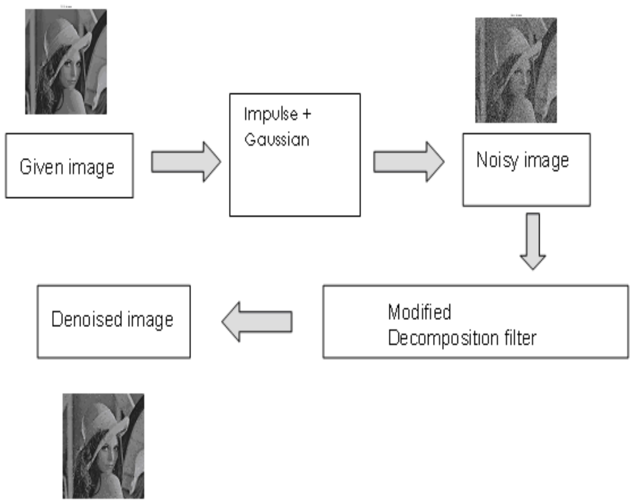


Fig.1. Insight of the proposed filter on mixed noises

3. PROPOSED WORK

In the existing threshold decomposition techniques, threshold levels from 0-255 are used, based upon which the pixels in the window are decomposed into strings of 1s and 0s, depending on whether the pixel intensity is greater than or lesser than the threshold level. Then the majority function is found out at each level which is recombined to produce the median value. The pixel to be processed is then replaced by the median value. Large number of threshold levels and bit comparisons are used in determining the majority function at each level, which increases the complexity of the process and the time taken for processing. The complexity of the process can be described as follows:

Stage 1: The stage involves the process of decomposing the pixels into 1s are required and 0s demands 256 one bit comparisons for each pixel.

Stage 2: The process of computing the majority function involves 9 one-bit comparisons at each threshold level. So, 256X9 comparisons are required for a 3X3 window.

Stage 3: 255 one bit comparisons are required for the process of recombining the 1’s, to obtain the median value.

3.1. PROPOSED ALGORITHM

The aim of the work is to apply the proposed filter over an image corrupted by mixed noises (zero mean Gaussian and impulse noise). Figure 1 denotes the aim of the work. To overcome this problem, a new algorithm is proposed in which the pixel intensity itself is considered as the threshold and decomposed into its equivalent string of 1s, thereby reducing the number of thresholds. The median is found eliminating the process of finding out the majority function which in turn eliminates the process of comparison. Proposed algorithm is given as follows:

STEP 1: A 2D window of size 3×3 is selected. Assume the pixel to be processed is p(x,y).

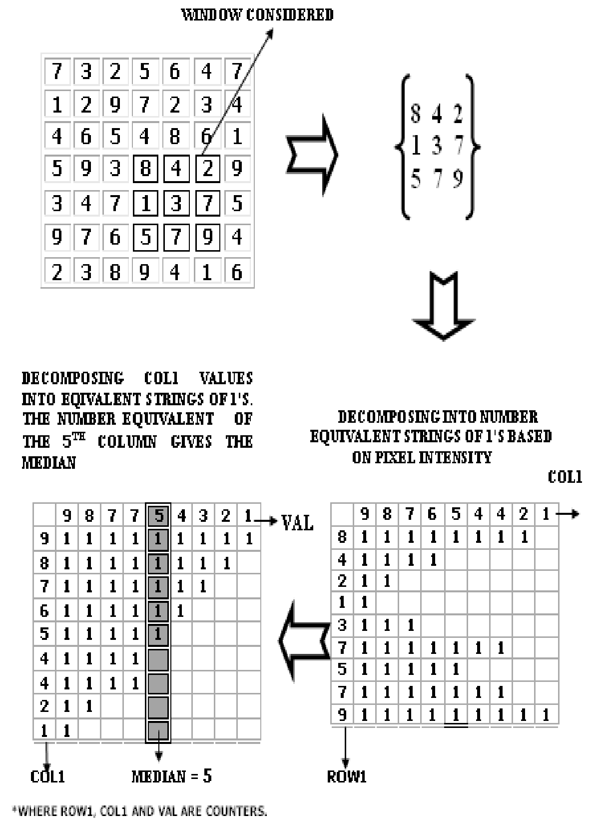


Fig.2. Methodology of the proposed algorithm

STEP 2: Every pixel of the window is decomposed into its number equivalent strings of 1’s considering the pixel intensity itself as the threshold. Here the decomposition is done with the help of a counter ROW1, which eliminates the comparison involved in decomposition process of the conventional and existing threshold decomposition techniques. Simultaneously, the number of 1’s in each column is counted with the help of a counter and its number equivalent is stored in COL1 simultaneously.

STEP 3: The values of COL1 counter are decomposed into its equivalent strings of 1’s and the number of 1’s at each column is recombined to obtain the pixel intensities of the window sorted in descending order with the help of counter VAL. The fifth element of the VAL or the number equivalent of the fifth column counter gives the median of the window considered. After the computation of median, the centre pixel of the window is replaced by the evaluated median. Subsequently, the window moves towards the right for a new set of window values; this processing as well as the updating procedure are repeated until the end of the image element is reached. Fig 2 denotes the methodology of proposed algorithm [1].

4. SIMULATION RESULTS

This Section experimentally analyzes the performance of developed image denoising algorithm with various median filters, such as, standard median filter(inbuilt MATLAB function) SMF, Center weighted median filter (CWF), Threshold decomposition filter (TDF), for Gaussian, Speckle and Salt & Pepper noise added on images such as Lena, Barbara, Baby, girl, Pepper and Cameraman image. It is experimentally proved that the proposed algorithm is as optimal for better denoising of different noises. Filtering performance can be evaluated by computing Peak Signal to Noise Ratio (PSNR),Image enhancement factor(IEF) and time using (matlab inbuilt functions) which are the estimates of the quality of a filtered image compared with an original image. The PSNR is calculated using the formulae.

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{MSE}\right)$$

$$\text{MSE} = \frac{\sum_{ij} r_{ij} - x_{ij}}{M \times N}$$

Where, r - Original image, MxN - size of image, x - restored image. The Image enhancement factor is calculated using the formulae

$$\text{IEF} = \frac{\left(\sum_{ij} n_{ij} - r_{ij}\right)^2}{\left(\sum_{ij} x_{ij} - r_{ij}\right)^2}$$

Where n - corrupted image, r - original image x - restored image [1].

The PSNR, IEF, and CPU computation time in seconds for impulse noise, zero mean Gaussian noise and Speckle noise are calculated for the PA and compared with SMF, CWF and TDF, in Tables 1 to 3 for lena.gif. The important aspect of the PA is that it uses a fixed 3X3 window for processing and thus leads to smaller computation time amongst the existing threshold decomposition filters or stack filters and centre weighted median filter. MATLAB 7.0(R14) on a PC equipped with 2-GHz CPU and 1GB of RAM memory has been employed for the evaluation of computation time of all algorithms. It was found from table1-3 that the proposed algorithm has better performance in removing impulse noise up to 30%.From table 5 and 6 it was observed that the proposed algorithm has capability to eliminate zero mean with 0.9% Gaussian noise and speckle noise up to 0.8%. Considering the discussions made before, Subsequent Tables 4 to 6 represents the performance of the SMF, CWF, TDF and PA for five different images by above said compositions of noises respectively. Table 7 and 8 shows the performance of the PA is better in terms of PSNR, IEF and optimum time when compared with SMF, CWF, and TDF for various types of images corrupted by all three types of noises in proportion. Fig 3-11 illustrates the performance of the PA over other filters for impulse noise, Gaussian noise and speckle noise. In fig 12-13 PA has higher PSNR, IEF when tested on different images which is corrupted by 30% impulse noise. In fig 15, 16 PA has slightly better PSNR, IEF over other filters that are used for denoising zero mean variance 0.9% Gaussian noise tested on various images. It was observed that for the images which have gray levels varying more (details of an image) such as cameraman.bmp, barbera.tif, girl.jpg the PA performance is average when compared with other filters. For the images whose gray levels is uniform(details of the image) such as baby.jpg, pepper.bmp the performance of the PA is good when compared with other filters. In fig 18 the PSNR performance of the PA is in par with other filters for 0.8% speckle noise. From fig 19 we understand such that depending upon the variation in grey levels in an image the performance is good or average. IEF of the PA good on par with other filters if the grey level changes are more else the performance is average. Fig 21-22 gives the performance of PA over different images corrupted by mixed noises in some proportion has a good PSNR and IEF. Fig 24-27 shows pictorial representation obtained by employing various filters. Fig 5, 8, 11, 14, 17, 20, 23 denotes the optimum computational speed at which the PA works.

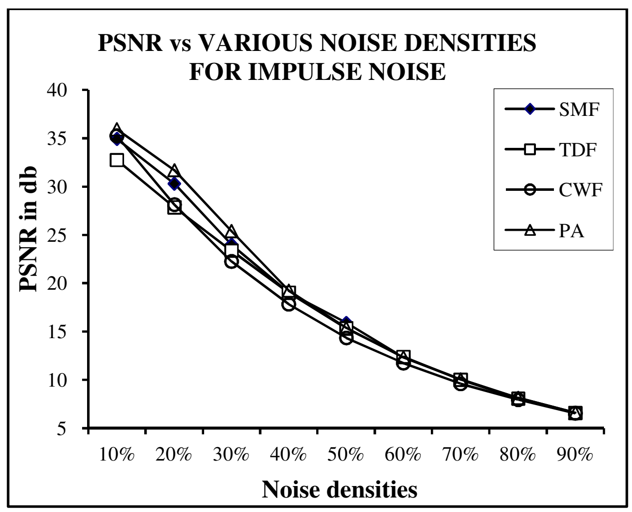


Fig.3. Noise density versus PSNR for various filters for Lena image corrupted by impulse noise

Table.1. PSNR, IEF, TIME for LENA.GIF (512 X 512) image corrupted by impulse noise at different noise densities

	PSNR				IEF				TIME			
ND	SMF	TDF	CWF	PA	SMF	TDF	CWF	PA	SMF	TDF	CWF	PA
10%	34.927	32.775	35.234	35.934	89.055	38.253	95.903	99.675	1.544	421.871	24.804	46.743
20%	30.305	27.841	28.136	31.713	61.079	25.055	37.278	67.702	1.404	441.934	20.545	45.968
30%	23.992	23.369	22.262	25.395	21.415	19.642	14.428	23.638	1.342	457.816	21.107	48.544
40%	19.023	19.012	17.853	19.238	9.181	9.226	6.947	9.586	1.373	481.09	28.548	49.024
50%	15.934	15.32	14.38	15.393	4.953	4.885	3.925	4.956	1.373	497.975	21.091	49.349

60%	12.36	12.42	11.748	12.357	2.958	2.986	2.572	2.946	1.357	509.552	19.375	49.347
70%	10.085	10.019	9.62	10.042	2.036	2.014	1.835	2.022	1.326	519.921	24.321	50.525
80%	8.159	8.103	7.973	8.143	1.496	1.483	1.429	1.492	1.388	519.314	21.185	50.774
90%	6.607	6.608	6.569	6.62	1.182	1.181	1.167	1.183	1.373	526.499	19.516	51.45

Table.2. PSNR, IEF, TIME for LENA.GIF (512 X 512) image corrupted by zero mean gaussian noise at different noise densities

	PSNR				**IEF**				**TIME**			
VAR	**SMF**	**TDF**	**CWF**	**PA**	**SMF**	**TDF**	**CWF**	**PA**	**SMF**	**TDF**	**CWF**	**PA**
0.001	34.08	29.384	34.092	34.126	2.656	1.078	2.575	2.597	1.444	227.29	34.092	40.863
0.002	32.403	28.807	32.211	32.438	3.462	1.806	3.315	3.49	1.458	233.09	32.211	41.049
0.003	31.213	28.307	30.909	31.229	3.963	2.328	3.699	3.983	1.513	239.424	30.909	40.216
0.004	30.276	27.841	29.931	30.341	4.232	2.745	3.927	4.314	1.414	245.428	29.931	40.184
0.005	29.557	27.406	29.163	29.577	4.487	3.038	4.102	4.494	1.583	252.896	29.163	40.352
0.006	28.926	27.051	28.473	28.972	4.622	3.319	4.2	4.692	2.014	256.614	28.473	41.337
0.007	28.361	26.653	27.921	28.405	4.739	3.508	4.274	4.768	1.38	265.054	27.921	40.49
0.008	27.919	26.386	27.434	27.923	4.854	3.682	4.382	4.881	1.387	265.209	27.434	40.573
0.009	27.434	26.064	26.982	27.544	4.906	3.849	4.398	4.993	1.379	275.593	26.982	40.415

Table.3. PSNR, IEF, TIME for LENA.GIF (512 X 512) image corrupted by speckle noise at different noise densities

	PSNR				**IEF**				**TIME**			
VAR	**SMF**	**TDF**	**CWF**	**PA**	**SMF**	**TDF**	**CWF**	**PA**	**SMF**	**TDF**	**CWF**	**PA**
0.001	36.488	29.912	36.986	36.507	0.741	0.218	0.838	0.744	1.355	216.164	18.224	39.99
0.002	35.612	29.749	35.936	35.681	1.212	0.409	1.304	1.224	1.364	218.575	14.692	39.92
0.003	34.922	29.579	35.088	34.973	1.548	0.582	1.609	1.565	1.334	219.502	16.421	39.758
0.004	34.309	29.411	34.379	34.394	1.796	0.734	1.819	1.827	1.375	229.621	12.792	40.243
0.005	33.844	29.283	33.797	34.217	2.007	0.875	1.992	2.007	1.327	225.588	14.246	39.717
0.006	33.348	29.114	33.299	33.362	2.152	0.998	2.128	2.166	1.356	228.329	12.888	39.722
0.007	32.917	28.957	32.822	32.955	2.27	1.109	2.219	2.286	1.332	233.477	13.516	39.796
0.008	32.541	28.806	32.413	32.599	2.283	1.219	2.31	2.41	1.384	229.223	13.9	39.719
0.009	36.488	29.912	36.986	36.507	0.741	0.218	0.838	0.744	1.355	216.164	18.224	39.99

Table.4. PSNR, IEF, TIME for different images corrupted by impulse noise at 30% noise density

IMAGES	**PSNR**				**IEF**				**TIME**			
	SMF	**TDF**	**CWF**	**PA**	**SMF**	**TDF**	**CWF**	**PA**	**SMF**	**TDF**	**CWF**	**PA**
BABY.JPG(292X425)	22.172	23.076	21.591	23.973	16.694	23.199	14.524	24.995	1.335	98.674	11.75	24.736
CAMERAMAN.BMP (256X256)	20.698	19.826	20.352	21.418	11.022	8.875	10.135	12.821	0.995	116.883	7.178	11.66
BARBERA.TIF (512X512)	21.038	21.327	20.041	21.147	10.917	10.075	8.722	11.239	1.38	457.713	14.24	62.22
PEPPER.BMP (512X512)	10.588	22.864	21.651	23.667	2.22	13.634	13.133	20.539	1.777	461.69	14.136	63.651
GIRL.JPG (600X900)	10.232	23.65	21.753	23.613	11.907	17.817	21.753	23.614	1.918	87.308	21.753	23.65

Table.5. PSNR, IEF, TIME for different images corrupted by zero mean Gaussian noise for variance 0.9

IMAGES	PSNR				IEF				TIME			
	SMF	TDF	CWF	PA	SMF	TDF	CWF	PA	SMF	TDF	CWF	PA
BABY.JPG (292X425)	27.744	27.821	27.34	27.917	4.952	3.964	4.489	5.111	1.354	91.194	19.62	27.116
CAMERAMAN.BMP (256X256)	24.361	21.778	25.651	24.427	2.246	1.266	2.15	2.292	0.017	82.554	25.199	11.245
BARBERA.TIF (512X512)	23.246	4.642	23.316	23.287	1.875	0.988	1.892	1.892	1.472	614.141	14.045	60.599
PEPPER.BMP (512X512)	20.657	25.566	26.669	27.065	1.128	2.148	4.043	4.472	1.656	136.334	14.281	62.035
GIRL.JPG (600X900)	20.839	26.973	32.285	27.366	2.116	2.778	1.939	4.584	1.782	211.644	69.512	79.246

Table.6. PSNR, IEF, and TIME for different images corrupted by speckle noise for variance 0.8%

IMAGES	PSNR				IEF				TIME			
	SMF	TDF	CWF	PA	SMF	TDF	CWF	PA	SMF	TDF	CWF	PA
BABY.JPG (292X425)	28.53	28.446	28.153	28.623	2.784	2.504	3.007	3.021	1.346	88.697	8.813	25.755
CAMERAMAN.BMP (256X256)	25.934	22.345	26.308	26.979	0.864	0.4	0.943	0.874	0.969	40.015	11.5	17.61
BARBERA.TIF (512X512)	24.523	24.969	24.842	24.563	0.52	0.42	0.558	0.522	1.157	166.657	23.062	69.656
PEPPER.BMP (512X512)	30.407	27.271	30.342	30.396	2.345	0.664	2.316	2.341	1.593	164.657	24.719	70.515
GIRL.JPG (600X900)	29.147	31.125	32.607	32.689	1.082	1.859	0.153	1.893	2.095	166.673	24.453	78.261

Table.7. PSNR, IEF, TIME for LENA.GIF, GIRL.JPG and BABY.JPG images corrupted by 20% impulse noise plus zero mean 0.9% variance Gaussian noise

	LENA.GIF(512X512)			GIRL.JPG(600X900)			BABY.JPG(292X425)		
	PSNR	IEF	TIME	PSNR	IEF	TIME	PSNR	IEF	TIME
SMF	24.599	16.596	4.14	12.14	9.238	5.056	24.145	17.386	3.699
CWF	22.631	10.569	39.798	22.51	11.413	60.134	22.676	12.6072	21.484
TDF	23.946	14.854	242.255	24.42	13.971	419.09	24.92	18.48	211.781
PA	24.704	17.015	113.295	24.643	18.591	183.885	25.074	20.999	66.235

Table.8. PSNR, IEF, TIME for BARBARA.TIF, PEPPER.BMP, CAMERAMAN.BMP images corrupted by 20% impulse noise plus zero mean 0.9% variance Gaussian noise

	BARBARA.TIF(512X512)			PEPPER. BMP(512X512)			CAMERAMAN.BMP(256X256)		
	PSNR	IEF	TIME	PSNR	IEF	TIME	PSNR	IEF	TIME
SMF	21.593	8.399	3.378	12.515	1.812	3.378	22.023	9.693	4.169
CWF	21.134	7.509	29.632	22.289	10.213	29.632	21.514	8.754	36.738
TDF	21.962	7.547	286.573	23.46	10.437	286.573	22.173	7.005	311.423
PA	21.987	8.565	150.454	24.244	16.011	150.454	22.274	10.59	155.469

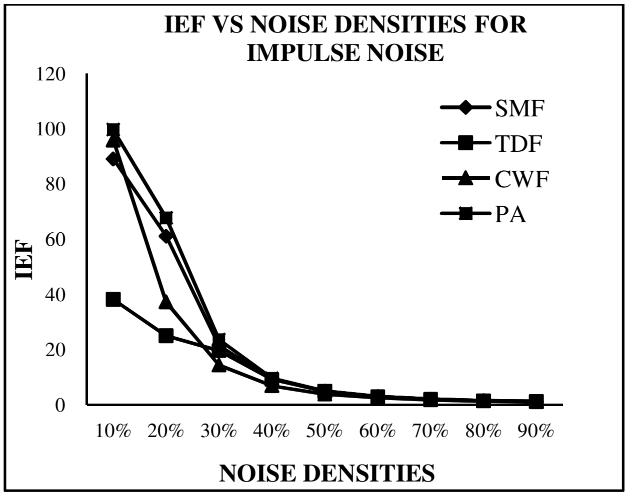


Fig.4. Noise density versus IEF for various filters for Lena image corrupted by impulse noise

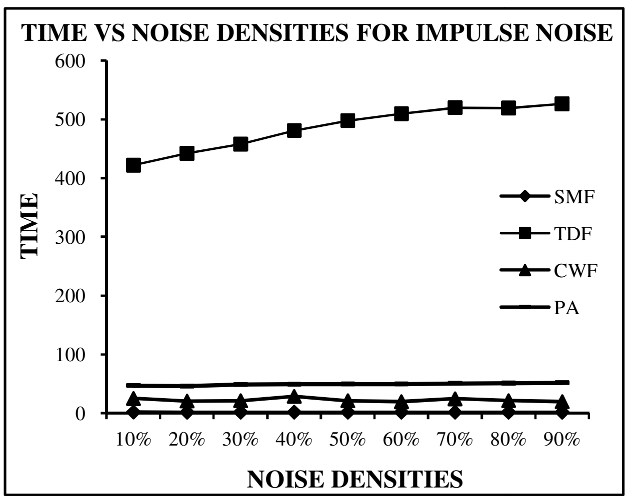


Fig.5. Noise density versus TIME for various filters for Lena image corrupted by impulse noise

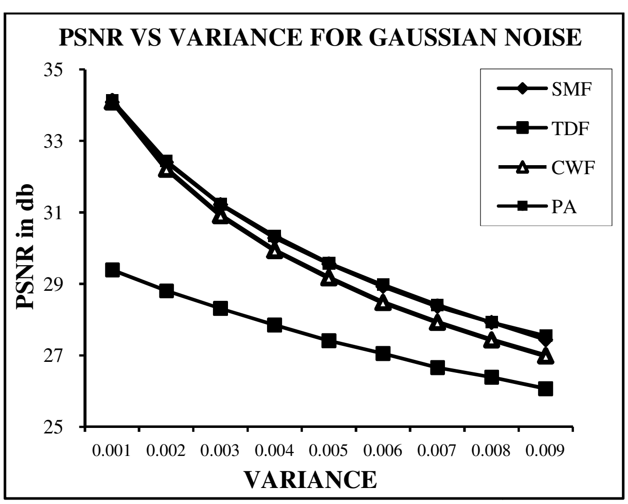


Fig.6. Variance versus PSNR for various filters for Lena image corrupted by Gaussian noise

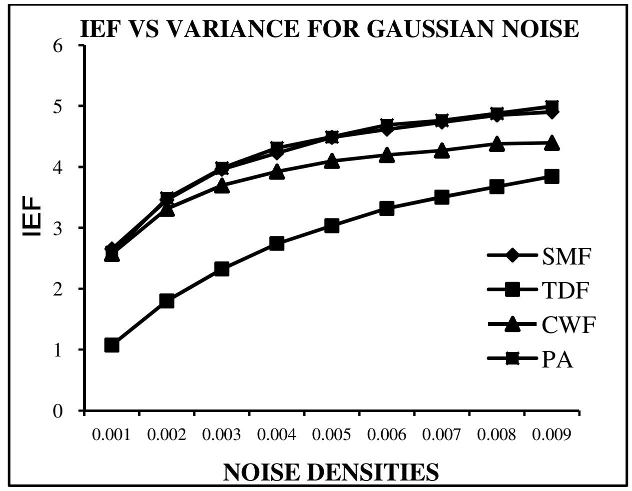


Fig.7. Variance versus IEF for various filters for Lena image corrupted by Gaussian noise

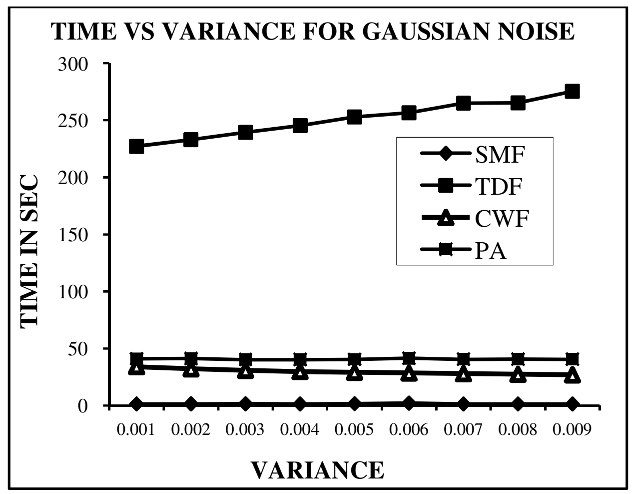


Fig.8. Variance versus TIME for various filters for Lena image corrupted by Gaussian noise

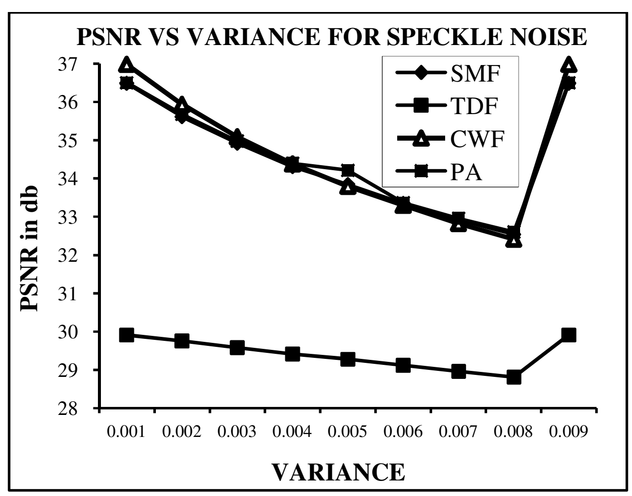


Fig.9. Variance versus PSNR for various filters for Lena image corrupted by Speckle noise

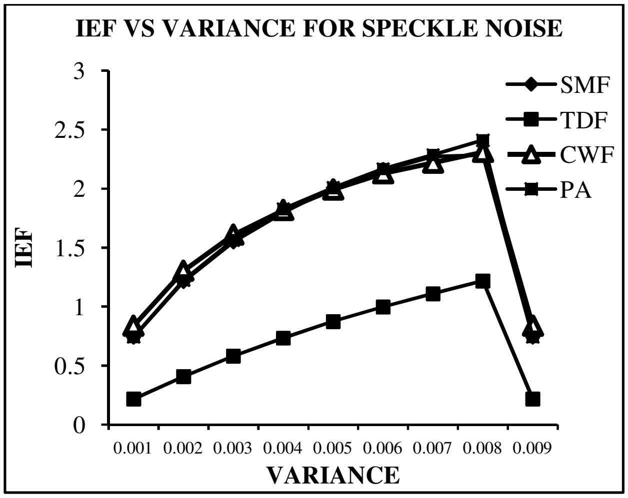


Fig.10. Variance versus IEF for various filters for Lena image corrupted by Speckle noise

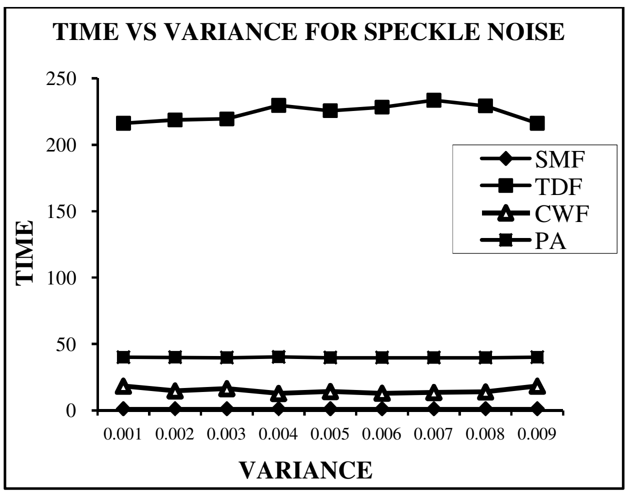


Fig.11. Variance versus TIME for various filters for Lena image corrupted by Speckle noise

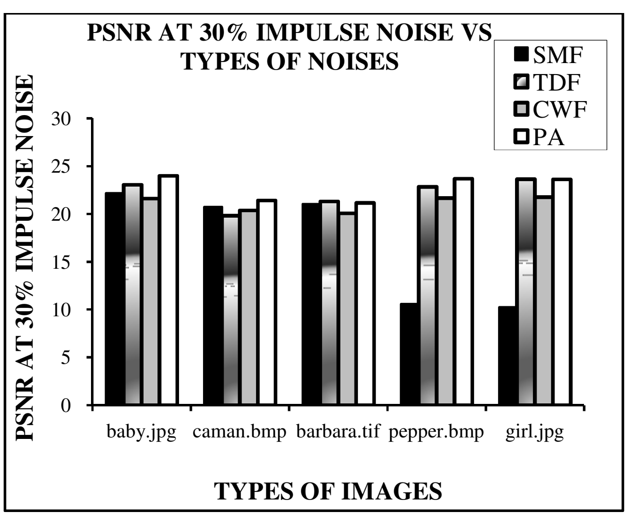


Fig.12. PSNR for various filters applied over different images corrupted by 30% impulse noise

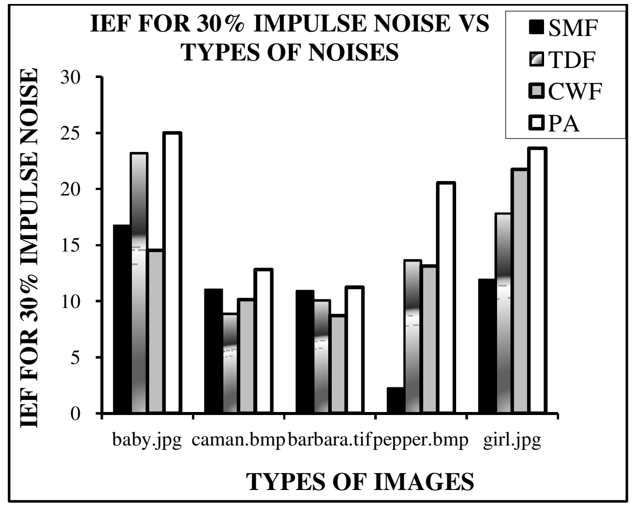


Fig.13. IEF for various filters applied over different images corrupted by 30% impulse noise

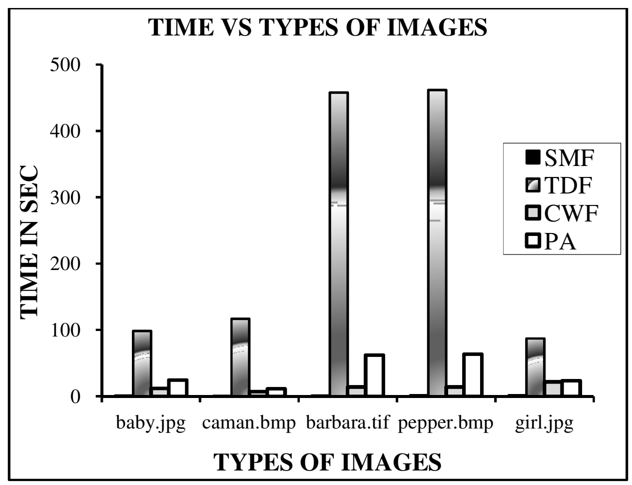


Fig.14. TIME for various filters applied over different images corrupted by 30% impulse noise

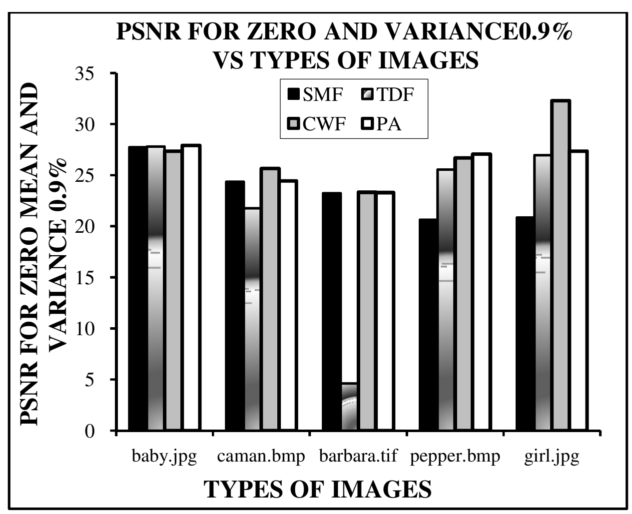


Fig.15. PSNR for various filters applied over different images corrupted by zero mean and 0.9% variance Gaussian noise

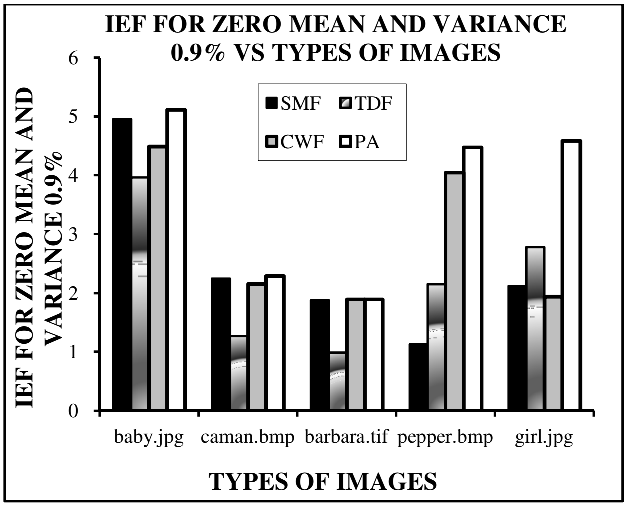


Fig.16. IEF for various filters applied over different images corrupted by zero mean and 0.9% variance Gaussian noise

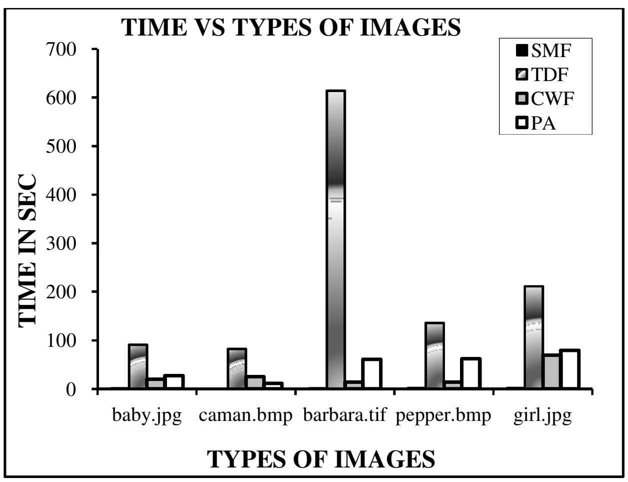


Fig.17. TIME for various filters applied over different images corrupted by zero mean and 0.9% variance Gaussian noise

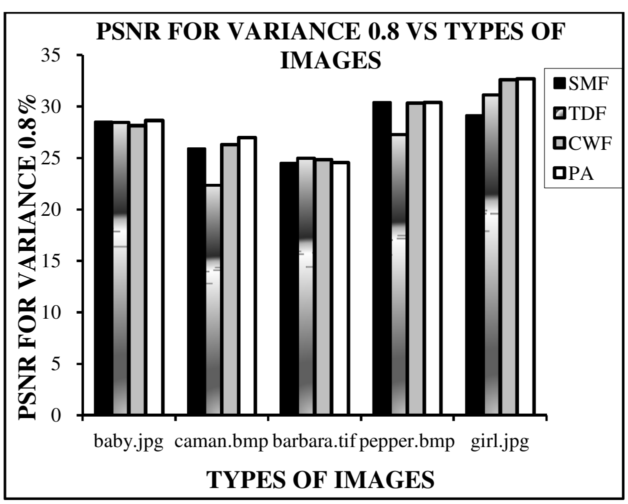


Fig.18. PSNR for various filters applied over different images corrupted by 0.8% variance Speckle noise

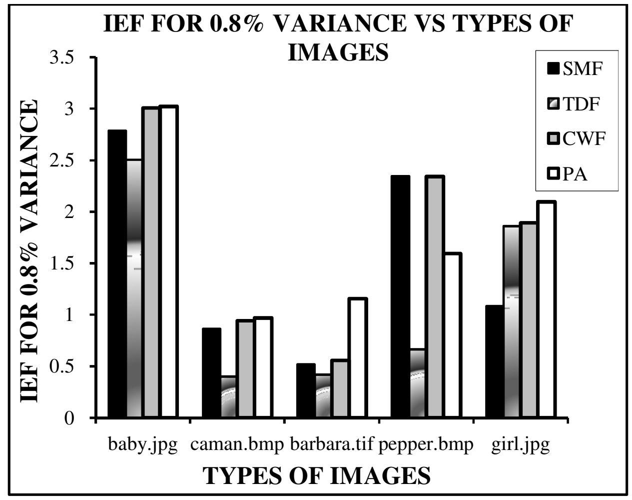


Fig.19. IEF for various filters applied over different images corrupted by 0.8% variance Speckle noise

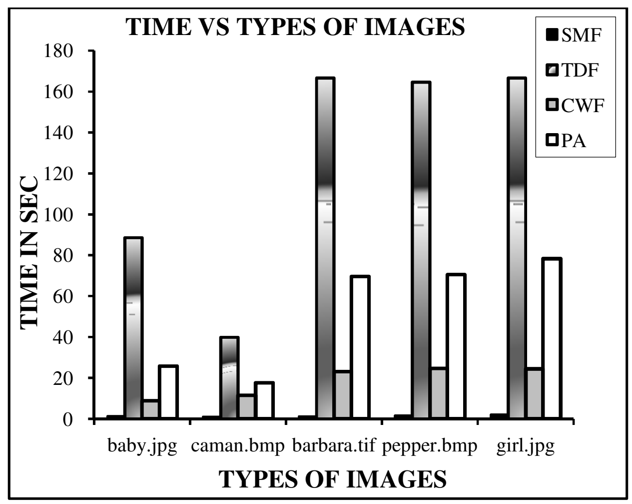


Fig.20. TIME for various filters applied over different images corrupted by 0.8% variance Speckle noise

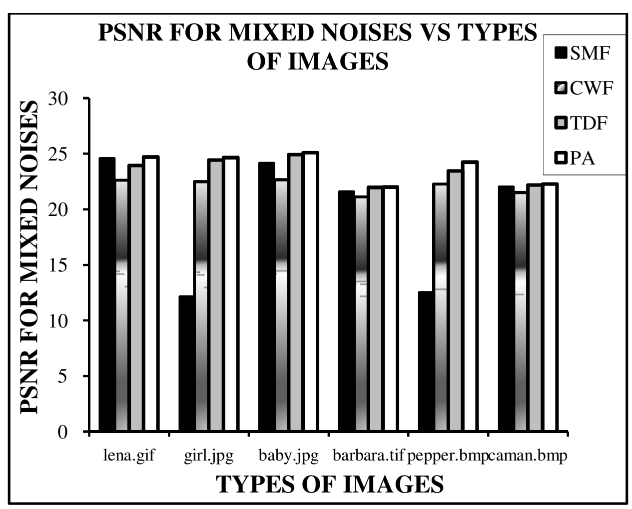


Fig.21. PSNR for various filters applied over different images corrupted by 20% impulse noise, 0.9%variance Gaussian noise

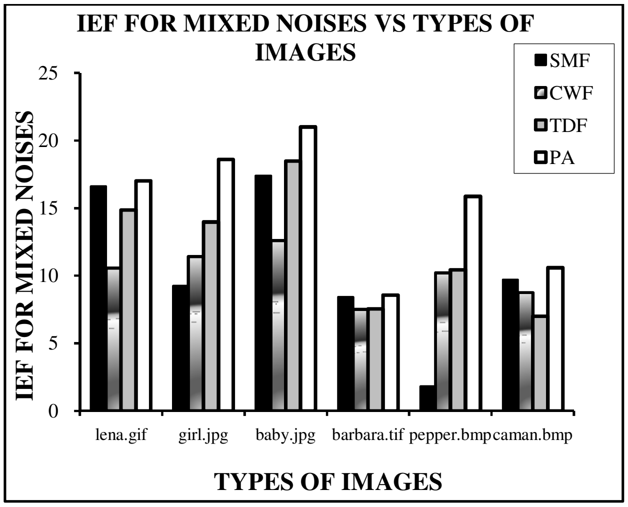


Fig.22. IEF for various filters applied over different images corrupted by 20% impulse noise, 0.9%variance Gaussian noise

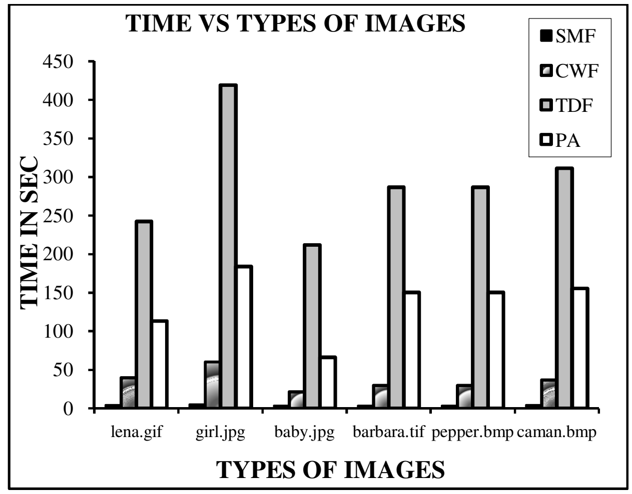


Fig.23. TIME for various filters applied over different images corrupted by 20% impulse noise, 0.9%variance Gaussian noise

(a) (b) (c) (d) (e) (f)

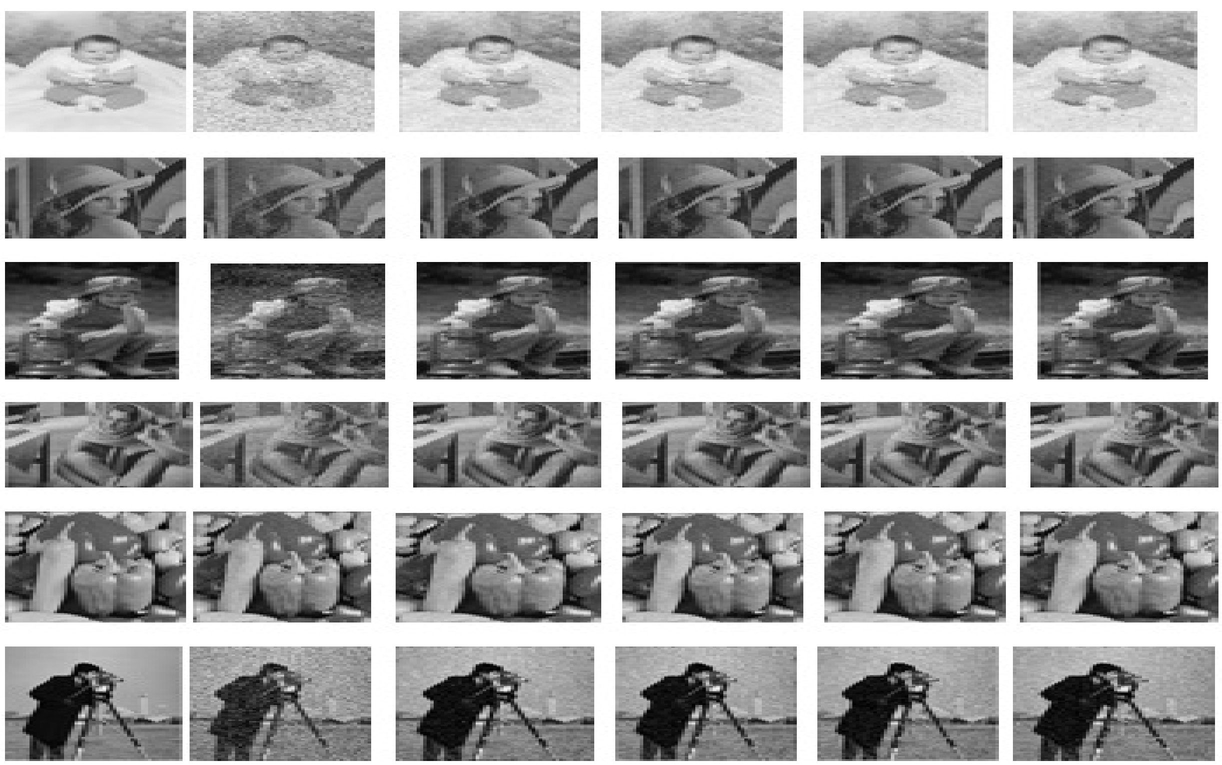
Fig.24. Cameraman.bmp, Barbara.tif, lena.gif (a) original image (b) impulse noise affected from by 30% (c) images restored by SMF (d) images restored from by TDF (e) images restored by CWF (f) images restored by proposed algorithm

(a) (b) (c) (d) (e) (f)

Fig.25. Cameraman.bmp, Barbara.tif, lena.gif (a) original image (b) Zero mean and 0.9% variance Gaussian noise (c) images restored by SMF (d) images restored from by TDF (e) images restored by CWF (f) images restored by proposed algorithm

(a) (b) (c) (d) (e) (f)

Fig.26. Cameraman.bmp, Barbara.tif, lena.gif (a) original image (b) 0.8% variance Speckle noise (c) images restored by SMF (d) images restored from by TDF (e) images restored by CWF (f) images restored by proposed algorithm



(a) (b) (c) (d) (e) (f)

Fig.27. Barbara.tif, pepper.bmp, lena.gif, Cameraman.bmp, baby.jpg, girl.jpg (a) original image (b) Impulse noise 20% plus zero mean 0.9% variance Gaussian noise (c) images restored by SMF (d) images restored from by CWF (e) images restored by TDF (f) images restored by proposed algorithm

5. CONCLUSION

From the exhaustive experiments, conducted for different noise types for different images for different median filters, we conclude that, the highest PSNR (dB) and IEF is not obtained for PA for different images and for different noise type. However, on overall basis, i.e., in an average sense, PA gives good performance for low density impulse noise up to 20%, zero mean 0.9% variance Gaussian noise removal. When compared to their class of decomposition filters such as TDF in specific, the PA exhibits better performance for Salt & Pepper noise removal up to 30% and reduces smaller proportion of zero mean 0.9% variance Gaussian noise. The proposed filter also exhibits good noise removal up to 0.8% speckle noise. In our method, time complexity of Threshold Decomposition is removed by considering the pixel intensity itself as threshold. Hence, the proposed method shows good performance with fewer complexities. The Proposed algorithm has good average computation time such that it's twice faster in comparison to TDF and exhibits optimum computation speed when compared with other filters.

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