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Image De-noising using PCA based Fusion and Neighbor Pixels Interpolation

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Abstract: An efficient technique has been proposed for de-noising the image that has greatly sorted the problem caused by the Random Value Impulse Noise (RVIN) in digital gray scale images. The proposed method consists of mainly two main phases: First phase detected the noise pixels using block wise dual threshold method. In the first phase, the boundary pixel has also been processed using interpolation techniques. The output image from the first phased is again processed to refine the corrupted pixels. The correct estimation of the original pixels at the place of corrupted pixels is done by Principal Component Analysis (PCA). Experimental results show the method has an outstanding performance than other state-of-the art the RVIN de-noising methods.

Keywords: RVIN; PCA; PSNR; MSE; pixel.

I. INTRODUCTION

Digital Image Processing is presentation its general application in the field of computer visualization and communication engineering. It has been developed in recent three decades and resulting an exponential increase in the need of transmission and storage requirement of image data. Image restoration is regarded as a very important and useful section of image processing [1]. It consists of algorithmic development and object oriented image processing. Images go through a variety of degradations during transmission acquisition and processing. Image restoration is a process of suppression or reduction of degradation that are occurred while the image is being processed. Image restoration is divided in to two sub-sections; image de-blurring and image de-noising. Noise corruption degrades the quality of an image along with other features like sharpness, edge, layer depth etc. Image de-noising refers to the process of recovering a good estimate of the original image from a corrupted one, without altering useful information in the image. Hence noise detection and its removal is incredibly vital image processing task for many applications. In this research, work is confined to image de-noising. In many image processing application, the Image de-noising is the fundamental, task to restore the image for better perception in the further processing. Over a last decade, it has been an interesting topic in image processing application. It is an important and fundamental step in the image preprocessing that recovers the original image or the best approximated or estimated from noisy data while preserving image details. However, so many diverse de-noising methods have been proposed in the literature. In this work, an automatic threshold based method has been proposed in aid with the median filter to de-noise the corrupted image from random value impulse noise [2].

A. Fundamental Concept of Image De-noising

For a digital computer, the input image is considered to be normal image. Therefore in order to deal the case of image de-noising methods, the type of the image degradation system and the noises are assumed to be known beforehand. Consider an input image f(x,y) and a degradation function H(x,y). When the image is passed through this degradation system, a noise is introduced during the process. Consider a degradation function together with the additive noise term applied on the input image (x, y). The process will produce the degraded image (x, y). Since the image (x, y) has been degraded. Therefore, along with knowledge about degradation function H(x,y) and some knowledge about the additive noise term $\eta(x, y)$, an estimate $f'(x, y)$ is obtained of the original image. A good restoration process should estimate $f'(x, y)$ of the original image f(x,y), that must be as close as possible as to the original input image [3]. The basic block of image degradation and restoration system is explained through the basic block diagram given in figure 1. Consider a degradation function H(x,y) and additive noise η. The degraded image is given as g(x,y). The Output image through $f'(x, y)$, which is closer to $f(x, y)$ is obtained through the knowledge of H and the additive noise η. If H is the transfer function of the degrading system, then the degraded image is obtained by $g(x, y) = H(x, y) \otimes f x, y + \eta(x, y)$

II. RELATED WORK

Previously there are many works take place in this field which is describe below

Firstly discuss about the Tri-state median filter in this they used the combination of standard median filter and centre-weighted median filter. Here by the use of this combination it identify whether the image is corrupted or not. If image is corrupted than find its threshold level and removed the destroyed image or pixels by use this combination of filters [4]. Secondly discuss about the RORD noise detector which is combined with simple weighted mean filter which is make an effective algorithm where this combination used to remove random valued impulse at randomly. In this propose

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method they used an image as reference image and apply this combination and restoration take place [5].

Thirdly discuss about removal of random value impulsive noise. Here to remove this type of noise we used Effective noise detector and a pixel-restoration operator. By the use of this combination a highly performance filter is deign which is removed RIN (Relative intensity noise) of the image. RIN is a biggest problem of researcher for a long time because they destroy the pixels of an image [6]. Another discussion used of recursive and adaptive median filter which is used to remove high density impulsive noise. In this method a centred noisy pixels used which is work as centre window if noise is not occur then we goes to another selected window or matrix. As we goes to next process if error not occur. Here they also make comparison this filter to another filter in the term of PSNR and IEF (image enhancement factor). Through this author achieve good result as compare to previous work [7]. Further discussion Adaptive Non-Local Switching Median (ANSM) detector used for the high noise densities. Based on the ASWM or this ANSM, a two-phase scheme is presented to remove random-valued impulse noise whether the noise level is low or not. More exactly, in the first phase, the adaptive switching median filter or the adaptive non-local switching median filter is used to recognize the noise candidates. In the second phase, only the noise candidates' values are restored by the edge-preserving regularization method. Simulation results show that the proposed two-phase scheme is considerably better to some of the state-of-the-art methods both visually and quantitatively with a noise level as high [8]. Final discussion on the adaptive dual threshold median filter which is used to remove random impulse value noise. In this method this filter is work on two stages which is noise detection and noise removal. For noise detection averaging based dual threshold method is used and for removal of noise simple median filter is used. By use of this the value of PSNR ratio is increased highly [9].

III. PROPOSED METHOD

In this work, the de-noising of image has been accomplished in to two phase. In first phase, an automatic threshold technique is adopted to find the noise pixel and a median based scheme is chosen to replace the new median filter. In second stage PCA based fusion is used.

A. *First Stage De-noising*

As seen, the single thresholding technique is not suitable techniques under the change in illumination variation. Since the variation in illumination may directly changes the pixels value, so a single boundary of separation is not suitable under such condition to resolve the problem. In this work, first the noise pixel is identified under a predefined size of the window. The window is selected using the parameter ‘m n’. Where the value of m and n have been chosen (3X3, 5X5 and 7X7) for experimental analysis. Initially, a mask of m X n is selected and the central pixel under the mask is investigated. The central pixel is examined whether it is noisy pixel or not. In order to examine the central pixel, a minimum and maximum boundary for an actual pixel is calculated. The minimum and maximum pixel range is calculated by averaging the rows and column pixels inside the mask. The calculated threshold values B_{min} and B_{max} are used to identify the existence of noisy pixel at the centre location of the mask. The centre pixel value of the mask is compared and the decision has been taken for the noisy pixel. The noisy pixel is detected using the following rule.

$$center\ pixel = \begin{matrix} noise\ free & if\ B_{min} < p_{22} < B_{max} \\ noisy & else \end{matrix} .(1)$$

In this manner, next mask is selected and the center pixel is treated for noisy and noise free value. All the pixel of the image is examined in order to identify the noise pixel. For each mask, the value of B_{min} and B_{max} are automatically updated. At the end of this stage, pixels which are corrupted by noise are identified and treated further in noise removal stage explained in following section. Image interpolation is the process to determine the unknown pixels or unprocessed filter based on some known pixels. As we know, the adjacent pixels has higher similarity , therefore last columns or rows pixels have been used to replace the boundary pixels [12].

B. *Noise Removal during Second Stage*

During the second phase, the filtered image from the first phase is rearranged using the mask of 3X3 and applying the median filter on it. Principal components analysis is a procedure that identify some important and a few number of uncorrelated variables, which are called "principal Components", from a large set of data [15]. The covariance matrix of the two images is calculated. The covariance matrix determines the covariance and similarity between the rows and columns of the two images. This gives the empirical description of two images. The next stage is to find the Eigen-values that are simply the coefficients which derive the eigenvectors. The significant principle components can be selected by ordering the Eigen-value from highest to lowest. By ranking their eigenvectors in order of their eigen-values, highest to lowest, the important data from the two images is selected. On the basis of the significant selection of eigen-value, its corresponding vectors are selected to estimate the final image. It uses the principle component of the two images. The two images are fused on the basis of the weight of the eigen vector.

C. *Experimental Analysis*

In this section, the simulation results of the proposed method are presented with the help some standard dataset. Before

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discussing the section, some quantitative evaluation parameter has been explained that justifies the results with respect, PSNR (Peak Signal to noise ratio), and MSE(Mean Square error).

The mean square error(MSE) and peak signal to noise ratio(PSNR) are defined by equations as follows:

$$MSE = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}[I(i,j) - K(i,j)]^2 (2)$$

$$PSNR = 10 \times log_{10}(\frac{255^2}{MSE}) (3)$$

Where, I and K are the original and reconstructed images.
The proposed method for the image de-noising is implemented using MATLAB 7.10 on 2.5 GHz processor of 4 GB RAM. Further, also the performance through this proposed method is investigated by changing the filtering window size.

All of the images are in JPEG format and the images of size 256 × 256 and 512x512 have been taken through this experiment. The performance of proposed image is checked by mixing the noise level for 10% to 70% noise density. In this experiment, the performance has been evaluated under the effect of speckle noise and Random valued impulse noise. From the experiment, it is seen that, our method achieves better PSNR and less MSE than other de-noising method reported in the literature. Figure 1 and 2 show the output of proposed method at various noise intensity level. Figure 1 shows the effect of filtering on lena image. In the above figures, 3X3 mask has been used. The PSNR at noise level 10% is better than at noise level 70%. The 3X3 filtering optimizes properly the corrected pixel value at noisy location. It is seen that the performance of filter degrades when noise level increases from 10 to 70%. It is clearly visible from the above figures, the visual quality of image becomes poorer when the percentage of noise quality decreases. The PSNR quality can be also judged with the quality of de-noised images. The qualitative and quantitative performance analysis of proposed image de-noising method using median based threshold computation and principle component fusion is also done on PEPPERS image. In figure 3 and 4, as one can visually inspect that the PSNR values are image dependent and decreases with increase in noise density. The PSNR values is maximum at 10% noise while lower at 70% noise. In Pepper image; the PSNR varies from 46.25 dB to 37.99 dB.

NOISY INTENSITY	NOISE IMAGE	DENOISE IMAGE	PSNR	MSE
10			40.58	23.19
30			39.17	31.55
50			37.50	46.34
70			35.77	69.00

Figure 1. De-noised Lena image using 3X3 mask at different noise intensity.

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IMAGE	NOISE IMAGE	DENOISE IMAGE	PSNR	MSE
10			52.83	1.36
30			46.32	6.08
50			42.66	14.12
70			39.63	28.41

Figure 2. De-noised Gold-hill image using 3X3 mask at different noise intensity.

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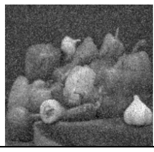
IMAGE	NOISE IMAGE	DENOISE IMAGE	PSNR	MSE
10			46.30	6.10
30			43.11	12.75
50			40.31	24.28
70			37.46	46.84

Figure 3. De-noised Pepper image using 3X3 mask at different noise intensity.

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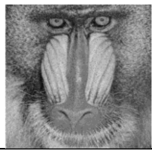
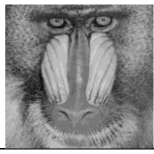
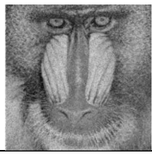
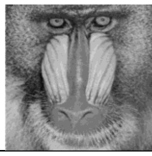
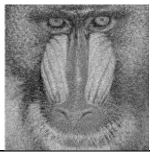
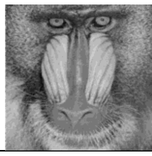
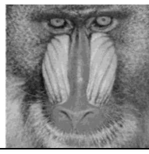
IMAGE	NOISE IMAGE	DENOISE IMAGE	PSNR	MSE
10			39.49	29.34
30			37.79	43.41
50			36.11	63.93
70			34.69	91.32

Figure 4. De-noised Mandrill image using 3X3 mask at different noise intensity.

Table I. PSNR comparison of proposed method using different noise level intensity

Filtering window dimension	10%	20%	30%	40%	50%	60%	70%
Lena							
3×3	40.58	39.93	39.17	38.31	37.50	36.69	35.77
5×5	37.25	37.10	36.78	36.43	36.00	35.55	34.92
7×7	35.19	35.17	34.95	34.64	34.68	34.03	33.46
Pepper							
3×3	46.30	44.54	43.11	41.74	40.31	38.82	37.46
5×5	42.78	42.38	41.54	40.69	39.68	39.08	37.98
7×7	40.52	40.08	39.52	38.13	38.01	37.43	36.61
Gold-Hill							
3×3	52.83	49.21	46.32	44.57	42.66	41.12	39.63
5×5	49.86	47.96	46.45	44.71	43.45	42.08	40.96
7×7	44.46	44.23	43.52	42.58	41.59	40.61	39.49
Mandrill							
3×3	39.49	38.82	37.79	36.76	36.11	35.39	34.69
5×5	33.53	33.49	33.41	33.20	33.01	32.75	32.52
7×7	31.52	31.50	31.47	31.36	31.20	30.94	30.88

Table II. MSE comparison of proposed method using different noise level intensity

Filtering window dimension	10%	20%	30%	40%	50%	60%	70%
Lena							
3×3	23.19	26.50	31.55	38.52	46.34	55.93	69.00
5×5	49.09	50.87	54.84	59.35	65.56	74.67	82.92
7×7	78.93	79.90	83.47	89.55	95.96	103.20	117.98
Pepper							
3×3	6.10	9.16	12.75	17.48	24.28	35.19	46.84

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5×5	13.76	15.08	18.32	22.23	28.01	32.43	41.61
7×7	23.12	25.62	29.12	33.90	39.60	47.15	56.94
Gold-hill							
3×3	1.36	3.12	6.08	9.10	14.12	20.13	28.41
5×5	3.23	4.96	5.90	8.81	11.78	16.14	20.90
7×7	9.044	9.85	11.60	14.74	18.07	22.68	29.63
Mandrill							
3×3	29.34	34.24	43.41	55.01	63.93	75.31	91.32
5×5	115.59	116.74	119.06	125.91	130.00	138.53	145.98
7×7	183.91	183.79	185.93	191.46	195.46	195.05	209.90

Table I and II show the PSNR and MSE value between at various noise density levels. The results in these table show that the PSNR value at low noise density is better at any size of window. However, the performance of filtering degrades as the noise level intensity increases. The overall performance of dual threshold based image de-noising based on principle components depends on the noise detection stage. The previous de-noising techniques were suffering from the total number of faulty detections that is the "Missed detection" and false detection. Moreover, by aiding the interpolation method, the performance of this filter has been improved greatly. Figure 5 and 6 show the PSNR and MSE value between at various noise density levels. The results in these graphs show that the PSNR value at low noise density is better at any size of window. The average PSNR of all image is found as 46.5 db using 3X3 mask at 10% noise level, while the average PSNR has been decreased to 36.5 db when the noise has corrupted 70% of the pixels using the same mask size. Using large size of mask improves the processing speed but decreases the PSNR. It is seen that when the mask size is increased to 7X7, the average PSNR is found to be 37.5 at 10% noise level, while when the noise is increased upto 70%, the PSNR fall to 33db.

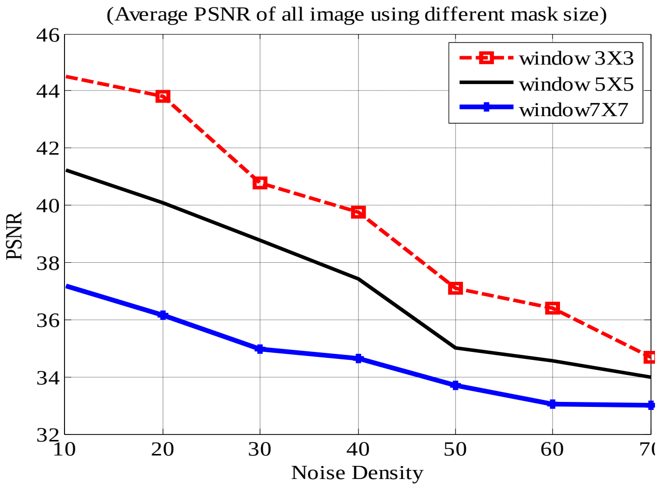

Figure 5. Average PSNR comparison of all images by varying mask size

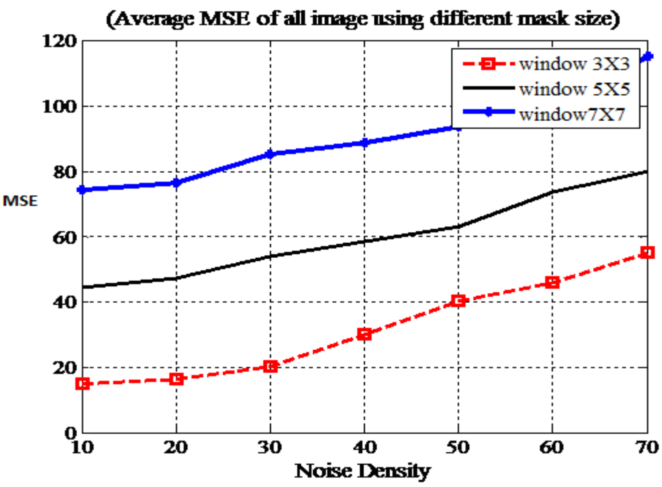

Figure 6. Average MSE comparison of all images by varying mask size

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Table III, IV, V and VI show the PSNR comparison between the proposed method and the other existing methods i.e. SM, TSM and ADTM at various noise density levels. The results show that the PSNR value at low noise density is better at low noise level at any size of window. However, the performance of filtering degrades with the increase of noise. The overall performance of the proposed method is better than other methods. In case of all image, the method has better detection and correction of noisy pixels than other methods.

Table III. Performance comparison of proposed method and other methods in terms of PSNR for Lena image

Methods	**Noise density 10%**	**Noise density 20%**	**Noise density 30%**	**Noise density 40%**	**Noise density 50%**	**Noise density 60%**	**Noise density 70%**
SM	30.46	28.85	27.16	25.38	24.30	22.91	21.21
TSM	36.87	32.37	30.50	28.48	25.39	23.52	20.21
ADTM	41.02	38.09	34.67	31.45	29.15	27.02	24.78
Proposed Method	40.58	39.93	39.17	38.31	37.50	36.69	35.77

Table IV. Performance comparison of proposed method and other methods in terms of PSNR for Pepper image

Methods	**Noise density 10%**	**Noise density 20%**	**Noise density 30%**	**Noise density 40%**	**Noise density 50%**	**Noise density 60%**	**Noise density 70%**
SM	30.05	28.32	26.82	25.38	23.97	21.01	20.02
TSM	32.05	31.34	27.62	23.17	20.20	18.85	17.52
ADTM	40.68	37.83	35.03	32.13	30.02	28.37	26.79
Proposed Method	46.30	44.54	43.11	41.74	40.31	38.82	37.46

Table V. Performance comparison of proposed method and other methods in terms of PSNR for Gold-hill image

Methods	**Noise density 10%**	**Noise density 20%**	**Noise density 30%**	**Noise density 40%**	**Noise density 50%**	**Noise density 60%**	**Noise density 70%**
SM	27.93	26.21	25.58	24.87	24.03	23.03	23.28
TSM	34.23	30.74	29.30	27.40	25.42	24.01	22.87
ADTM	36.91	35.38	33.25	31.78	29.84	28.22	26.74
Proposed Method	52.83	49.21	46.32	44.57	42.66	41.12	39.63

Table VI. Performance comparison of proposed method and other methods in terms of PSNR for Mandrill image

Methods	**Noise density 10%**	**Noise density 20%**	**Noise density 30%**	**Noise density 40%**	**Noise density 50%**	**Noise density 60%**	**Noise density 70%**
SM	28.81	27.43	25.49	23.62	22.59	21.50	19.80
TSM	32.36	29.22	26.08	24.27	23.48	21.20	20.01
ADTM	35.93	34.39	32.77	31.59	29.87	28.69	26.51
Proposed Method	39.49	38.82	37.79	36.76	36.11	35.39	34.69

IV. CONCLUSION

The qualitative and quantitative performance analysis of proposed image de-noising method using median based threshold computation and principle component fusion is also done on standard images. The PSNR and MSE results of proposed method are calculated. As one can visually inspect that the PSNR values are image dependent and decreases with increase in noise density. The PSNR values has maximum at 10% noise while lower at 70% noise. It is clearly

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visible from the above figures, the visual quality of image becomes poorer when the percentage of noise quality decreases. The overall performance of dual threshold based image de-noising based on principle components depends on the noise detection stage. It is seen that in previous literature, the existing methods have no capability to detect the noise. The previous de-noising techniques were suffering from the total number of faulty detections that is the "Missed detection" and false detection. Moreover, by aiding the interpolation method, the performance of this filter has been improved greatly. The PSNR comparison is shown between the proposed method and the other existing methods i.e. SM, TSM and ADTM at various noise density levels.

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