LAYER DISCRIMINATION WITH NON-ZERO ADJACENT ELEMENT AND PIXEL RESTORATION WIENER FILTER APPROACH FOR IMPULSE & POISSON NOISE REMOVAL FROM X-RAY IMAGES

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ABSTRACT: *In this paper, we propose a layer discrimination with non-zero and pixel restoration wiener filter approach to remove impulse and Poisson noise from X-ray image. Many filters have been used for impulse noise removal from color and gray scale images with their own strengths and weaknesses but X-ray images contains Poisson noise and unfortunately there is no intelligent filter which can detect impulse and Poisson noise from X-ray images. Our proposed filter use layer discrimination with non-zero adjacent element elimination approach to detect both Impulse and Poisson noise corrupted pixels in X-ray images and then restore only those detected pixels with wiener filter in a simple way. Our Proposed algorithms are very effective and much more efficient than all existing filters used only for Impulse noise removal. The proposed method uses a new powerful and efficient noise detection method to determine whether the pixel under observation is corrupted or noise free. If it is corrupted then restore it with wiener filter in second step while those uncorrupted pixels are remaining unchanged. Results from computer simulations are used to demonstrate pleasing performance of our proposed method.*

Keywords: X-ray Image De-noising, Impulse Noise, Poisson Noise,

INTRODUCTION

Digital images may be corrupted by impulse noise in some applications. Attenuate noise is an essential task in digital image processing. The most important thing of this task is how to reduce noise while keeping the image details. There are many works on the restoration of images corrupted by impulse noise. The most popular impulse noise filter is median filter [1] but it smears some details and edges of original images especially when the noise level is high. Different remedies of the median filter have been proposed, such as weighted median filter [2] center weighted median filter [3]. These filters apply median operation to each pixel regardless if the current pixel is contaminated or not, while this operation could produce serious image blurring and can suffer noise free pixels.

Early developed switching median filters often provide good outputs only at smaller noise levels [4]. A soft-switching impulse detector at the expense of computational complexity works on highly corrupted noisy images [5]. The Progressive Switching Median Filter (PSMF) involves in numerous iterations bringing down the computational efficiency [6]. [7] Proposes a more efficient Switching Median Filter (Krishnan filter) based on [8,9], which makes possible a perfect removal of impulse noise from images corrupted with salt and pepper noise and maintains a good computational efficiency.

These noise detection processes often lead to incorrect discrimination between pixel and noise. The noise adaptive soft-switching median (NASM) filter was proposed in to address this issue [10]. The NASM achieves robust performance in removing impulse noise while noise ranging from 10% to 50%. However, for those corrupted images with noise density greater than 50%, the quality of the recovered images become significantly degraded.

BDND perform well and can achieve pleasing result even noise density up to 90% [11]. However, it is too time-consuming to be used in real applications. Directional switching median filter detect only impulse noise corrupted pixel in same way like BDND but with a bit modification [12]. BDND with Square root approach design and work in same way like the rest but with a bit changing in detection process can only use for Impulse noise detection and restoration [13].

In this paper, we proposed a novel LDNzAdEE algorithm to detect Impulse and Poisson noise corrupted pixels in an efficient, fast and in most

reliable way and then restore those detected pixels with a second novel PRWF algorithm. PRWF algorithm will restore all detected pixels in a very simple and efficient way and it will de-blur the image as well. The quality of the filtered images is more prominent than BDND, BDND by Elimination, and BDND with Square root approach.

2. IMPULSE & POISSON NOISE DETECTION METHOD

In this section, first, we will discuss about different Impulse and Poisson noise models and then at the end we will discuss about our proposed noise detection algorithm.

2.1. Impulse noise models

2.1.1. Noise model 1

Pixels are randomly corrupted by two fixed extreme values "0" and "255" generated with the same probability. That is, for each image pixel at location (i, j) with intensity value $s_{i,j}$, the corresponding pixel of the noisy image will be $x_{i,j}$, in which the Probability Density Function of $x_{i,j}$ is

$$f(x) = \begin{cases} P/2, & \text{for } x = 0 \\ 1 - P, & \text{for } x = s_{i,j} \\ P/2, & \text{for } x = 255 \end{cases} \quad (1)$$

Where 'P' is the noise density.

Equation 1 shows that each pixel in an image has probability *P/2"* to be corrupted into either a white dot (salt) or a black dot (pepper) and has a probability "*1-p"* to be noise-free pixels or clean pixels. The binomial distribution is the discrete probability distribution of the number of successes in a sequence of "*n'* independent yes/no experiments, each of which yields success with probability "*p"*. Thus, in a window, if "*n"* represents the number of trials i.e. total number of pixels and "*r"* represents the number of success i.e. pixels corrupted with noise having a probability "*p"* and probability "*1-p"* for noise free pixels, then the Probability Density Function *f(x)* of an image corrupted with impulse noise can also be expressed as

$$f(x) = \binom{n}{r} p^r (1-p)^{n-r} \qquad (2)$$

In this proposed method, the noise density within the placed window size is calculated by using the equation for probability expressed as the ratio of number of impulses (NA) to the total number of pixels (N), mathematically expressed as

$$f(x) = N_A/N \qquad (3)$$

2.1.2. Noise model 2

Model 2 is similar to Model 1, except that each pixel might be corrupted by either "pepper" noise (i.e.0) or "salt" noise (i.e. 1) with unequal probabilities. That is,

$$f(x) = \begin{cases} P1, & \text{for } x = 0 \\ 1-P, & \text{for } x = s_{i,j} \\ P2, & \text{for } x = 255 \end{cases} \qquad (4)$$

$p = p1 + p2$ is the noise density and $p1 != p2$

2.1.3. NOISE MODEL 3

Instead of two fixed values, impulse noise could be more realistically modeled by two fixed ranges that appear at both ends with a length of *m* each, respectively. For example, if *m* is 10, noise will equal likely be any values in the range of either [0, 9] or [246, 255]. That is,

$$f(x) = \begin{cases} P/2m, & \text{for } 0 <= x < m \\ 1-P, & \text{for } x = s_{i,j} \\ P/2m, & \text{for } 255-m < x <= 255 \end{cases} \qquad (5)$$

'P' is the noise density.

2.1.4. Noise model 4

Model 4 is similar to Model 3, except that the densities of low-intensity impulse noise and high-intensity impulse noise are unequal. That is,

$$f(x) = \begin{cases} P1/m, & \text{for } 0 <= x < m \\ 1-P, & \text{for } x = s_{i,j} \\ P2/m, & \text{for } 255-m < x <= 255 \end{cases} \qquad (6)$$

$p = p1 + p2$ is the noise density and $p1 != p2$

2.1.5. Noise model 5 (Poisson noise)

Poisson noise can affect X-ray image pixels intensity value with any random value of (m) respect to the neighbouring pixel i.e. pixel can get any random value. That is,

$$f(x) = \begin{cases} P1/m & \text{for } 0 <= x <= m \\ 1-P = S_{i,j} & \\ P2/m & \text{for } 255-m <= x <= 255 \end{cases} \qquad (7)$$

2.2. Layer discrimination using non-zero adjacent element elimination (LDNzAdEE) algorithm

Our proposed algorithm is applied to each pixel of a noisy X-ray image in order to identify whether the pixel is 'corrupted' or 'noise free'. A two-dimensional binary decision Metrics is formed at the end of the detection phase; with'0 'indicating the position of uncorrupted pixels and'1', indicating the position of corrupted ones.

The proposed process consists of two iterations, in which the second iteration will called conditionally. In summary, the steps of the proposed detection method are as follows:

1. Read Noisy X-ray Image & Impose 7*7 Window around i^{th} & j^{th} pixel and Create a Binary Map (BM) of same sub Image.
2. Store all the values under the window in a vector (V) and Sort it in ascending order.
3. Find Lowest & Highest values in Vector V.
4. From Lowest to (Lowest + Highest) / 2, Compute the difference of Non-Zero adjacent pixels in V and store it in Vector D.
5. Find the maximum difference in D **(From Lowest to (Lowest + Highest) / 2)** & Mark its corresponding pixel in V as b1.
6. Similarly, from (Lowest + Highest) / 2 to Highest, Compute the difference of Non-Zero adjacent pixels in V and store it in Vector D.
7. Find the maximum difference in D **(From Lowest + Highest) / 2 to Highest)** & Mark its corresponding pixel in V as b2.
8. If selected pixel belongs to **middle cluster** then Uncorrupted. Set corresponding location in BM as "0" and go to step 10. ELSE
9. Invoke 2^{nd} iteration and impose 3*3 window on same pixel and go to step 2.
10. End. (move to next pixel to check where corrupted or not)

As compared to BDND (PE Ng, K. K. Ma, 2006), BDND by elimination (A. Nasimudeen, et al., 2012) and BDND by square root calculation (M Ashima, A Tayal, 2012), our proposed approach is more robust and reliable. By using Non-zero adjacent element elimination and with Lowest/Highest idea, we can remove a lot of unnecessary comparison that ultimately improve calculation speed and can detect Poisson noise corrupted pixels as well.

Beside all these advantages, at the end we will restore all detected pixels with a novel Pixel Restoration Wiener Filter approach, which is quite simple, very fast and are well suited to remove blurriness from X-ray image.

As we studied that all the existing system/approaches used median filters families like switching median filter, directional median filter or Decision based median filter etc but all these approaches are supposed to be used for removing impulse noise only and no one can handle Poisson noise effect from X-ray images like image blurriness. PRWF can handle restoration of all detected pixels and image blurriness in an efficient way.

For the understanding of the algorithmic steps mentioned above, a 5×5 windowed sub image (instead of 7×7) with the center pixel "165" is used as an example for illustrating the proposed detection process in figure 1.

3. PIXEL RESTORATION WIENER FILTER ALGORITHM

Steps for PRWF are as follow:

1. Firstly, Pixel x_{ij} is selected from image X,
   Then in same way b_{ij} is selected from binary map BM, where i = 1 to (M −1) and j = 1 to (N −1) for an image of size MxN. (BM already constructed during 1st algorithm)
   If b_{ij} ='0', then pixel x_{ij} is 'uncorrupted'. Hence, go to step 5 ELSE go to 2.
2. Select a 3X3 window W_x in X and W_b in BM centered around $(i,j)^{th}$ pixel x_{ij} in X and b_{ij} in BM respectively.
3. Check for '0's (uncorrupted pixels) in W_b and store corresponding elements of W_x in vector Z.
4. If Z is a null vector, go to step 5. Else, replace x_{ij} with Wiener of vector Z.
   x_{ij} = Wiener (Z)
5. Increment i,j and consider next x_{ij}, b_{ij} and go to step 2.

4. EXPERIMENTAL RESULTS

The performance of the proposed filter is tested against BDND, BDND by elimination, and BDND with square root filter on a variety of standard test images. Objective comparisons of the performances of these filters on images corrupted by various impulse noises and Poisson noise are made with the Peak Signal to Noise ratios (PSNR) of the images restored by them. Table 1 shows miss detection and false alarm and Table 2 represents PSNR results for all existing and proposed approaches

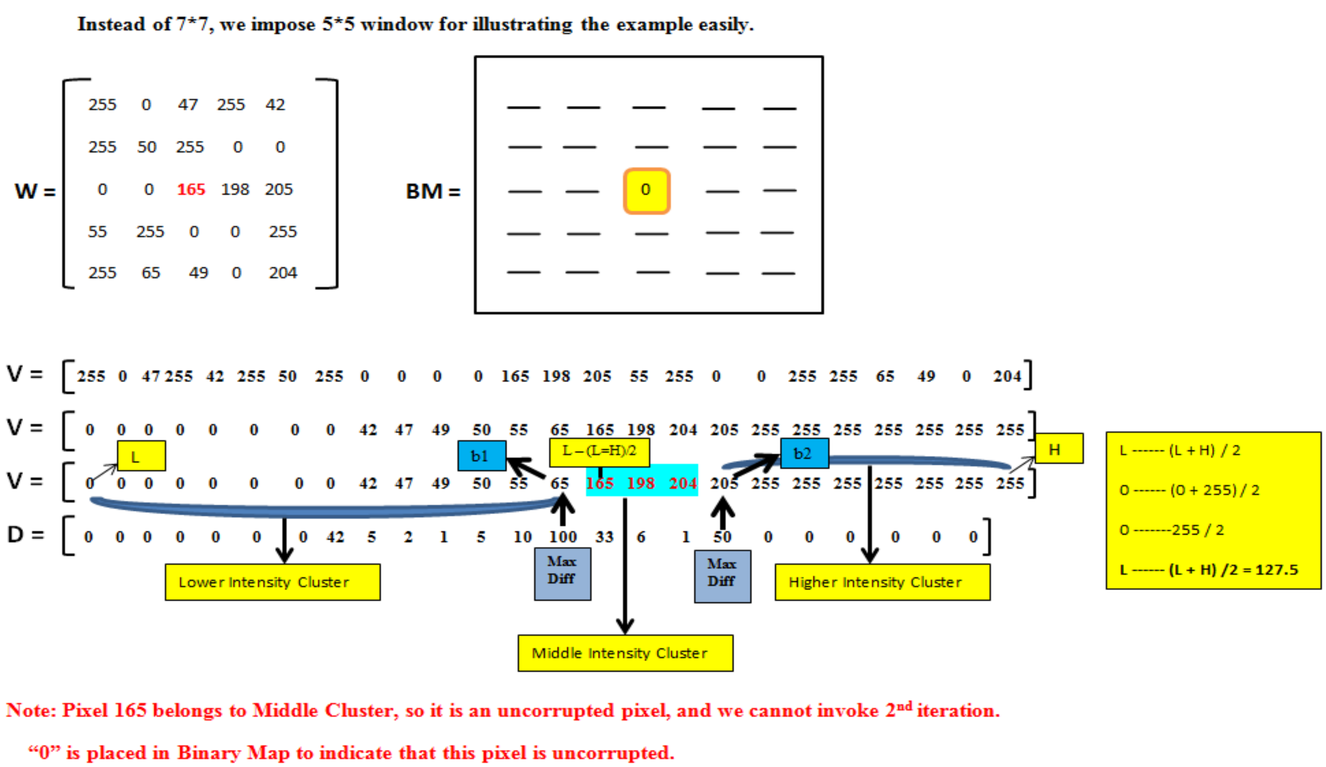

Figure 1. LDNzAdEE Algorithm Example

For our experiments, we used intel Pentium core i5 computer and grayscale images with 8 bit and with 256*256 resolution.

Table 1. Shows Miss Detection and False Alarm

Technique / Noise Type	Impulse Noise with Density 20%	Impulse Noise with Density 90%	Poisson Noise with Density 20%	Poisson Noise with Density 90%
BDND	Miss Detection 0 False Alarm 224	Miss Detection 0 False Alarm 447	Miss Detection 80 False Alarm 511	Miss Detection 119 False Alarm 745
BDND by Elimination	Miss Detection 0 False Alarm 180	Miss Detection 2 False Alarm 328	Miss Detection 51 False Alarm 425	Miss Detection 68 False Alarm 654
BDND with square root	Miss Detection 0 False Alarm 160	Miss Detection 0 False Alarm 298	Miss Detection 180 False Alarm 354	Miss Detection 235 False Alarm 691
LDNzAdEE	Miss Detection 0 False Alarm 47	Miss Detection 0 False Alarm 67	Miss Detection 12 False Alarm 80	Miss Detection 47 False Alarm 91

Now we can check PSNR results in Table 2.

Table 2. Shows PSNR results

Technique / Noise Type	Impulse Noise with Density 20%	Impulse Noise with Density 90%	Poisson Noise with Density 20%	Poisson Noise with Density 90%
BDND	MSE: 18.3970 PNSR: 31.9730	MSE: 26.7637 PNSR: 34.7875	MSE: 29.1188 PNSR: 29.5231	MSE: 33.1989 PNSR: 25.9594
BDND by Elimination	MSE: 15.2528 PNSR: 28.9730	MSE: 22.9906 PNSR: 30.0008	MSE: 28.0419 PNSR: 30.8444	MSE: 30.5816 PNSR: 27.8353
BDND with square root	MSE: 18.3811 PNSR: 29.7895	MSE: 23.1122 PNSR: 27.9182	MSE: 29.8589 PNSR: 28.5620	MSE: 32.8782 PNSR: 25.0663
Proposed Approach	MSE: 12.7873 PNSR: 35.2779	MSE: 14.1472 PNSR: 34.8153	MSE: 22.5806 PNSR: 36.7944	MSE: 26.1737 PNSR: 28.0898

The results in the table show that our proposed approach provides the best results.

5. CONCLUSION

In this paper, we propose a fast and reliable algorithm for impulse and Poisson noise detection, experimental results show that our method performs better than all cited filters. The tremendous advantage of the proposed method is that it is simple and can be realized even faster than all existing filters and can detect corrupted pixels in an efficient and reliable way. To remove blurriness from X-ray image, our PRWF algorithm outperforms all existing approaches.

REFERENCES

[1] Huan, T. S., Yang, G. J., and Tang G. Y. 1979. "Fast two-dimensional median filtering algorithm," IEEE Trans. Acoustics, Speech, *Signal Process*, vol. **ASSP-1**, no. 1, pp. 13–18, Jan. 1979.

[2] Yang, R., Lin, L., Gabbouj, M., Astola, J., Neuvo, Y. 1995. "Optimal weighted median filters under structural constraints," *IEEE Trans.Signal Processing*, vol. **43**, pp. 591–604, Mar. 1995.

[3] Song, T., Gabbouj, M., Neuvo, Y. 1994. "Center weighted median filters: some properties and applications in image processing," *Signal Processing*, vol. **35**, no. 3, pp. 213–229, 1994.

[4] Sun T., Neuvo, Y. "Detail-preserving median based filters in image processing", *Pattern Recognit. Lett*, vol.**15**, pp.341C347, April 1994.

[5] Abreu, E., Lightstone, M., Mitra, S. K., K Arakawa, K. 1996. "A new efficient approach for the removal of impulse noise from highly corrupted images", *IEEE Trans. Image Processing*, vol. **5**, pp. 1012-1025, 1996.

[6] Wang, Z., Zhang, D., "Progressive switching median filter for the Removal of impulse noise from highly corrupted images", *IEEE Trans Circuits and Systems-II: Analog and Digital Signal Processing*, vol. **46**, no.1, Jan.1999.

[7] Nallaperumal, K., Varghese, J., et al., 2007. "An efficient Switching Median Filter for Salt & Pepper Impulse Noise Reduction", *Proc. Of IEEE ICDIM* 2006, Bangalore, India, April 2007.

[8] Nallaperumal, K., Krishnaveni, K., Varghese, J., et al., "Fuzzy Optimal threshold Multiscale Morphological Segmentation of Digital Image", *Proc. of IEEE WOCN* 2006 Bangalore, India, April 2006.

[9] Nallaperumal, K., Varghese, J., et al., 2006. "Selective Switching Median Filter for the Removal of Slat & Pepper Noise", *Proc. Of IEEE WOCN*, Bangalore, India, April 2006.

[10] Eng, H. L., Ma, K. K., "Noise adaptive soft-switching median filter," *IEEE Trans. Image Processing*, vol. **10**, pp. 242- 251, Feb 2001.

[11] Ng, P. E., Ma, K. K., A Switching Median Filter With Boundary Discriminative Noise Detection for Extremely Corrupted Image", *IEEE Trans. Image Processing*, Vol. **15**, No. 6, June 2006.

[12] Nasimudeen, A., Nair, S., Madhu, Tatavarti, R., 2012. "Directional switching median filter using boundary discriminative noise detection by elimination", *Signal*, *Image and Video Processing*, Volume **6**, Issue 4, pp 613-624, November 2012.

[13] Ashima, M., Tayal, A., "Impulse Noise Detection and Filtering in Switching Median Filters", *International Journal of Computer Applications* (0975 – 8887) Volume **45**– No.13, May 2012.