Sādhanā Vol. 42, No. 6, June 2017, pp. 855–863
DOI 10.1007/s12046-017-0654-4

Poisson noise reduction from X-ray images by region classification and response median filtering

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MS received 18 May 2015; revised 28 November 2016; accepted 7 January 2017

Abstract. Medical imaging is perturbed with inherent noise such as speckle noise in ultrasound, Poisson noise in X-ray and Rician noise in MRI imaging. This paper focuses on X-ray image denoising problem. X-ray image quality could be improved by increasing dose value; however, this may result in cell death or similar kinds of issues. Therefore, image processing techniques are developed to minimise noise instead of increasing dose value for patient safety. In this paper, usage of modified Harris corner point detector to predict noisy pixels and responsive median filtering in spatial domain is proposed. Experimentation proved that the proposed work performs better than simple median filter and moving average (MA) filter. The results are very close to non-local means Poisson noise filter which is one of the current state-of-the-art methods. Benefits of the proposed work are simple noise prediction mechanism, good visual quality and less execution time.

Keywords. Poisson noise; modified Harris operator; response matrix; region classification; response median filtering.

1. Introduction

X-ray is a very popular low-cost medical imaging modality. This modality is used to detect fractures in bones, tumours, cough or pneumonia and dental issues. X-rays are produced using photons. These photons have wavelength <0.2–0.1 nm and has high penetration ability. Nowadays, X-ray images are produced using a digital receptor. X-ray image formation is statistical in nature. The photons, film holder, receptor and patient follow Poisson processes. These Poisson processes result in degradation of X-ray quality, which is known as Poisson noise. Dose value could be increased further to reduce Poisson noise; however, it has been limited by a medical term known as maximum permissible dose (MPD). Dose of X-ray should not exceed MPD limit for patient safety. Hence, instead of increasing dose, image quality could be improved by using image denoising algorithms.

Image denoising is a classical problem; various solutions are available with their advantages and limitations. Denoising issue could be handled in spatial domain or transform domain independently; however, a combination of both domains is possible and termed as hybrid approach. Most of the algorithms assume image noise is Gaussian and additive in nature. Tomasi and Manduchi [1] proposed a bilateral filter for Gaussian noise removal. Concept of photometric distance and geometric distance was used in their paper. Buades *et al* [2] suggested a “non-local mean” (NLM) algorithm in which they worked on a patch-based concept. This algorithm is iterative in nature. Dabov *et al* [3] presented a state-of-the-art method “block matching and 3D filtering,” popularly known as BM3D. This method is based on hybrid approach. All the aforementioned techniques are current state-of-the-art techniques and proved their performance better in spatial domain for additive Gaussian noise reduction. However, practically noise is not restricted to additive Gaussian nature. It could be multiplicative e.g. speckle noise, or signal dependent e.g. Poisson noise. Therefore, developments for specific noise-dependent algorithms are desired.

This research lays emphasis on Poisson corrupted X-ray images. Hence, literature survey cited here is restricted to Poisson noise reduction techniques. Poisson noise could be handled in two ways. First one is deploy Poisson statistics for denoising techniques and second is usage of variance stabilisation transform (VST) to adapt noise distribution from Poisson to Gaussian. This modification in distribution offers benefit to use conventional denoising algorithms. Deledalle *et al* [4] suggested modifications in NLM filter using Poisson statistics. However, this is an iterative technique and requires large execution time. Similarly, the BM3D algorithm is modified by Makitalo and Foi [5] for Poisson noise reduction. In that paper, Anscombe transform is used to stabilise the variance of Poisson-corrupted images and then regular BM3D algorithm is used. This algorithm has high complexity. Other than these state-of-the-art

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techniques, a few Poisson reducing algorithms are mentioned which compared with proposed algorithm.

Wang *et al* [6] proposed improved Bayes shrink (IBS) threshold for medical images using Daubechies wavelet transform. In this paper, edge preservation is obtained using preprocessing with adaptive size wiener filter. Subbuthai *et al* [7] proposed work for dental X-ray images using simple median filtering compared to Gaussian and FIR filter. Authors claimed that simple median filtering is superior over Gaussian and FIR filtering irrespective of noise type (Salt and Pepper, Speckle and Poisson are considered in that work). Lingyan Du *et al* [8] used dual tree complex wavelet transform (DTCWT) for Poisson noise reduction from X-ray images. Direction selectivity of DTCWT is better than wavelet transform, hence results are improved. Jisha and Suresh Kumar [9] proposed an algorithm for Poisson noise reduction in medical images. Their work is based on a combination of Curvelet transform and multi-scalevariance stabilization transform (VST). Curvelet transform gives better characterisation for curves and singularities as compared to wavelet transform. Multi-scale VST remaps the noise distribution towards Gaussian. Therefore, this combination gives better performance over wavelet transform.

This paper is outlined as follows. Section 2 contains material and methods, in which section 2.1 explains briefly about Poisson noise and section 2.2 includes some basics of Harris operator. Section 3 explains the proposed methodology with modified Harris operator, region classification and response median filtering. Section 4 presents the results and comparisons with existing techniques, followed by conclusions and future scope.

2. Material and methods

X-ray image formation includes Poisson noise. Poisson noise follows Poisson distribution, which is explained in section 2.1. Identification of noisy and noise-free pixels using modified Harris detector is described in section 2.2.

2.1 *Brief about Poisson noise*

Noise is an undesirable signal which gets added in a desired signal at the time of acquisition. In images, noise can modify the intensity level of a single pixel or a bunch of pixels, which results in poor quality image. Noise has additive or multiplicative type of nature. Even though the nature of noise is random, it follows some specific distribution. Main source of Poisson noise is collection of photons at the receptor side in a random manner. Poisson noise follows Poisson distribution, which is defined by Eq. (1) and its nature is shown in figure 1.

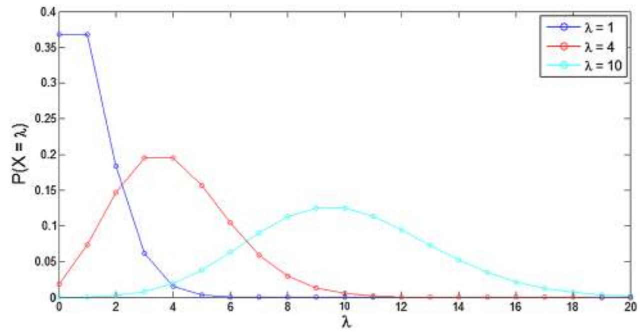


Figure 1. Nature of Poisson distribution at different λ values.

$$F(k;\lambda) = P(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}; \quad k = 0, 1, 2, \ldots, \infty \quad (1)$$

where $\lambda = E(X) = \mathrm{Var}(X)$, e is the base of the natural logarithmic function and k is the number of successes we are interested in.

2.2 *Harris operator*

Harris and Stephens [10] proposed the Harris corner detector. This is popular as Harris operator, sometimes known as Harris gradient detector. It takes advantage of different image regions such as flat region, corner points and edges. This region classification is based on Eigen values of response matrix, which are labelled as λ1, λ2 in figure 2.

Response matrix calculation is a very important step in Harris operator. Response matrix gives intensity variation of candidate pixel compared with neighbourhood pixels. It denotes value 1 if maximum intensity variation is detected, else 0 is stored in response matrix. In this process, candidate pixel is compare with other pixels according to mask size. Harris operator calculates intensity variation using local autocorrelation function as given in the following equation.

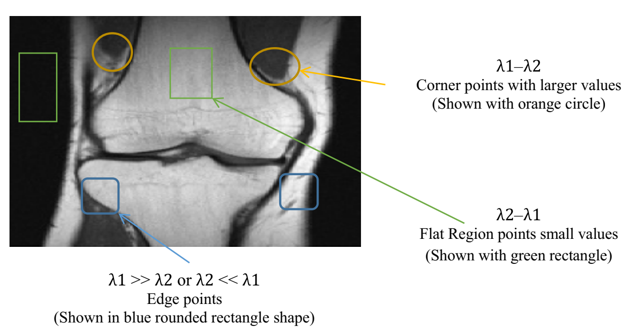
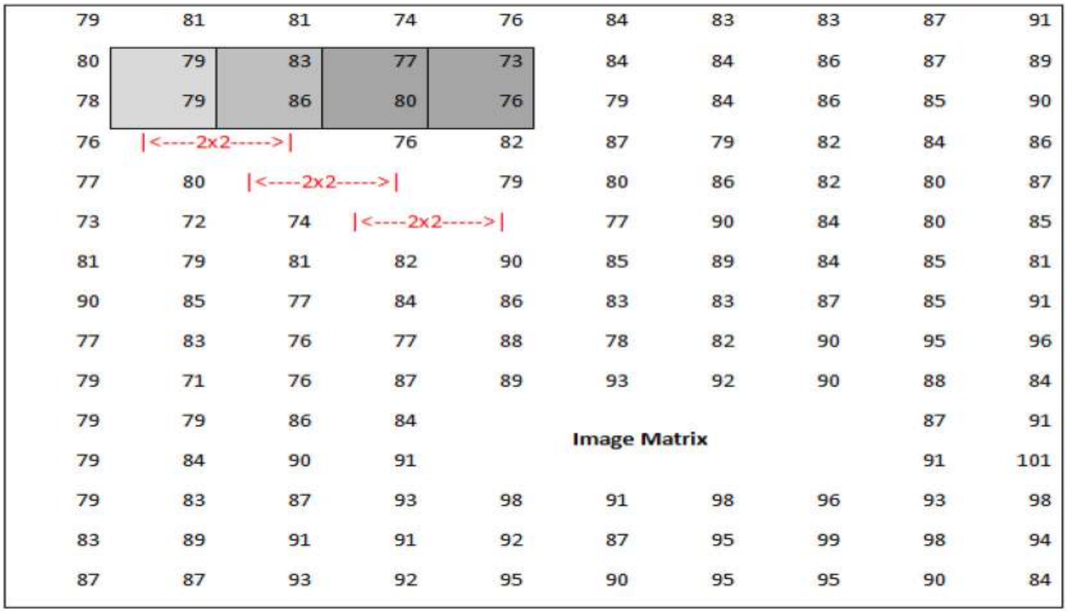


Figure 2. Basic idea of Harris operator for different values of λ1, λ2.



79	81	81	74	76	84	83	83	87	91
80	79	83	77	73	84	84	86	87	89
78	79	86	80	76	79	84	86	85	90
76	|<----2x2----->|		76	82	87	79	82	84	86
77	80	|<----2x2----->|		79	80	86	82	80	87
73	72	74	|<----2x2----->|		77	90	84	80	85
81	79	81	82	90	85	89	84	85	81
90	85	77	84	86	83	83	87	85	91
77	83	76	77	88	78	82	90	95	96
79	71	76	87	89	93	92	90	88	84
79	79	86	84					87	91
					Image Matrix				
79	84	90	91					91	101
79	83	87	93	98	91	98	96	93	98
83	89	91	91	92	87	95	99	98	94
87	87	93	92	95	90	95	95	90	84

Figure 3. Modifications in Harris operator.

$$\mathrm{EV}(a,b) = \sum M(i,j) * [X(i+a,j+b) - X(i,j)]^2 \quad (2)$$

where $M(i, j)$ = windowing function, $X(i + a, j + b)$ = shifted intensity and $X(i, j)$ = original intensity.

Response matrix is calculated as per Eq. (3), representing inclusion of intensity variation calculated by gradient detection.

$$R = \mathrm{Det}(H) - k * (\mathrm{Trace}(H))^2 \quad (3)$$

where H is the Harris matrix

$$H = \begin{bmatrix} \mathrm{Ix2(x,y)} & \mathrm{Ixy(x,y)} \\ \mathrm{Ixy(x,y)} & \mathrm{Iy2(x,y)} \end{bmatrix} \quad (4)$$

Ix = gradient of image in X-direction

Iy = gradient of image in Y-direction

Ix2 = Ix*Ix, Ixy = Ix*Iy, Iy2 = Iy*Iy

We have suggested modifications in this basic Harris detector, which is explained in section 3.

3. Proposed methodology

In this section, 3.1 explains modification in Harris operator and 3.2 explains region classification and response median filtering used in proposed algorithm. Section 3.3 highlights the proposed algorithm.

3.1 *Modified Harris operator*

Harris operator with odd size mask e.g. 3 × 3 and 5 × 5, is used in the watermarking to find corner points. However, this basic Harris operator is not suitable for image denoising application. Therefore, we proposed modifications explained in our earlier work by Thakur *et al* [11]. It includes 2 × 2 even-size mask instead of odd-size mask. Image is scanned with this mask in overlapped fashion as shown in figure 3 to get maximum number of noisy pixels, which is prime requirement of denoising technique.

Image matrix is scanned using modified Harris operator, then the response matrix is calculated. Response matrix contains only 1 and 0 for different pixel values of given host X-ray image. Response matrix denotes value 1 for a pixel having maximum intensity variation compared to its neighbors. Similarly, value 0 represents less intensity variation compared to its neighbours. This fact is used for prediction of noisy and noise-free pixels. Consequently, value 1 in response matrix indicates noisy pixel and zero indicates noise-free pixel. Figures 4 and 5 depict X-ray image and its respective response matrix image.

Accuracy of noise prediction is tested by adding noise synthetically in noise-free image. The procedure is as follows:

Step 1: Take original image in Matrix A.
Step 2: Matrix B = Matrix A + Poisson noise.

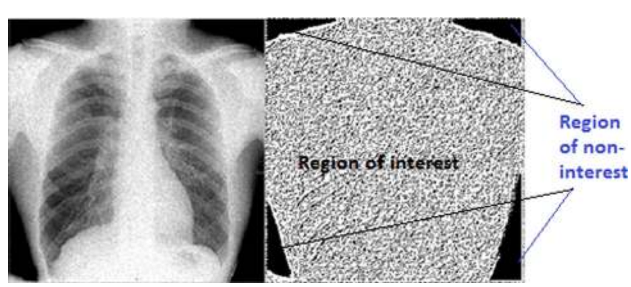


Figure 4. Chest X-ray image and its response matrix image.

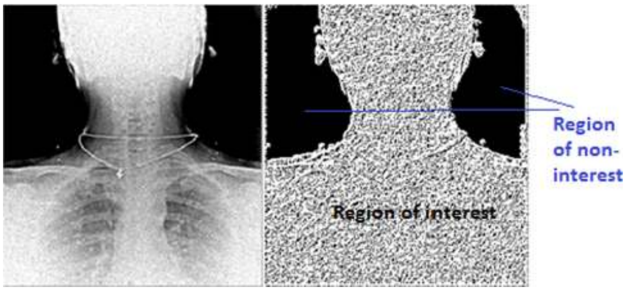


Figure 5. Neck X-ray image and its response matrix image.

Table 1. Percentage accuracy of algorithm for noise prediction.

Image	Total no. of pixels	Actual no. of noisy pixels	Noisy pixels detected by our algorithm	Difference in both	% extra noisy pixels detected
Spine	262,144	130,734	135,500	4766	3.64
Hand	262,144	125,319	139,056	13,737	10.96
Dental	262,144	130,612	134,513	3901	2.98
Chest	262,144	243,212	197,807	−45,405	−18.66*
Knee	262,144	131,368	135,539	4171	3.17

*Less number of pixels predicted than actual noisy pixels.

Step 3: Matrix C = Matrix A − Matrix B.
Step 4:

if Matrix C $\neq$ 0
Matrix C = 1;
else
Matrix C = 0;
End

Step 5: Actual noisy pixels = no. of 1's in Matrix C.
Step 6: Find response matrix for noisy image (Matrix B) using modified Harris Detector.
Step 7: Compare actual noisy matrix with response matrix.
Step 8: Calculate percentage of correctly detected noisy pixels.

Table 1 highlights the prediction accuracy of response matrix. Positive value in the last column reflects extra prediction of noisy pixels, whereas negative sign (refer row 5 and last column in table 1) indicates fewer pixels predicted than actual noisy pixels.

3.2 *Region classification and response median filtering*

Region classification includes differentiating area of interest from area of non-interest, which is shown for chest and neck X-ray images in figures 4 and 5 respectively. In general, effect of noise is not visible for low-intensity region of X-ray images, hence this region is not involved in denoising. Modified Harris operator assigns 0 values in response matrix for the area of non-interest. Hence, these respective pixels kept unprocessed in proposed algorithm. On the other hand, area where noise is dominantly visible, response matrix assigns 1 value. Those locations are processed in proposed algorithm. Thus, occurrence of 1 and 0 in response matrix is responsible for classifying the noisy and noise-free regions. Figure 6 shows the response matrix of image and classified region.

Denoising is performed using response median filter in proposed algorithm. Median filter is non-linear filter used for eliminating Poisson noise with advantage of edge preservation. Modification in median filter is

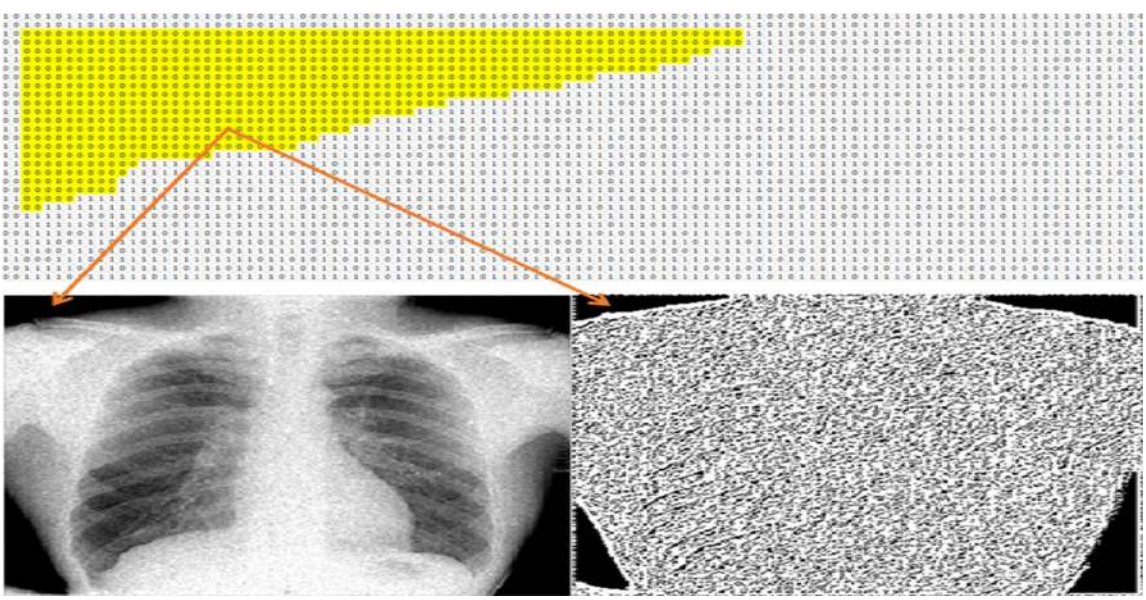


Figure 6. Response matrix and its location with respect to image.

proposed by Fabijanska and Sankowski [12], Nallaperumal *et al* [13], and Ng and Ma [14]. Many authors identify noisy pixel in the first step, then median filtering is performed on the detected pixels. This is known as adaptive switching median filtering. In this paper, decision to denoised particular pixel is depends on response matrix. Hence, proposed filter is labelled as "response median filter."

3.3 *Proposed algorithm*

Figure 7 indicates block diagram of proposed work. Blockwise modified Harris operator is applied on noisy X-ray image and a response matrix is generated. Response matrix predicts noisy and noise-free pixels along with region of interest and non-interest. Mean and median filters combination is applied to locations deduced from response matrix to get noise-free image.

Algorithm of proposed work is as follows:

1. Take host noisy X-ray image.
2. Apply Harris operator and find out response matrix of corresponding X-ray image.
3. Identify region of interest and region of non-interest.
4. If R $(x, y) = 1$ (that is corresponding host image pixel HI (x, y) is noisy).
   - Pick up eight neighbour connected pixel from host image

HI $(x-1, y-1)$	HI $(x-1, y)$	HI $(x-1, y+1)$
HI $(x, y-1)$	HI (x, y)	HI $(x, y+1)$
HI $(x+1, y-1)$	HI $(x+1, y)$	HI $(x+1, y+1)$

   - Find out median of them
   - Put new image pixel NI (x, y) as median in previous step

   Else NI (x, y) = mean (HI(x, y))

5. Calculate quality metric PSNR using formula given in the following equation.

$$\mathrm{PSNR} = \frac{10 * \log_{10}(\mathrm{Imax} * \mathrm{Imax})}{\mathrm{MSE}} \tag{5}$$

where Imax = maximum grey value of image.

MSE is mean square error and calculated as

$$\mathrm{MSE} = \frac{1}{M * N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} [\mathrm{OI}(i,j) - \mathrm{NI}(i,j)]^2 \tag{6}$$

where OI = original image and NI = denoised image. M and N are dimensions of original image.

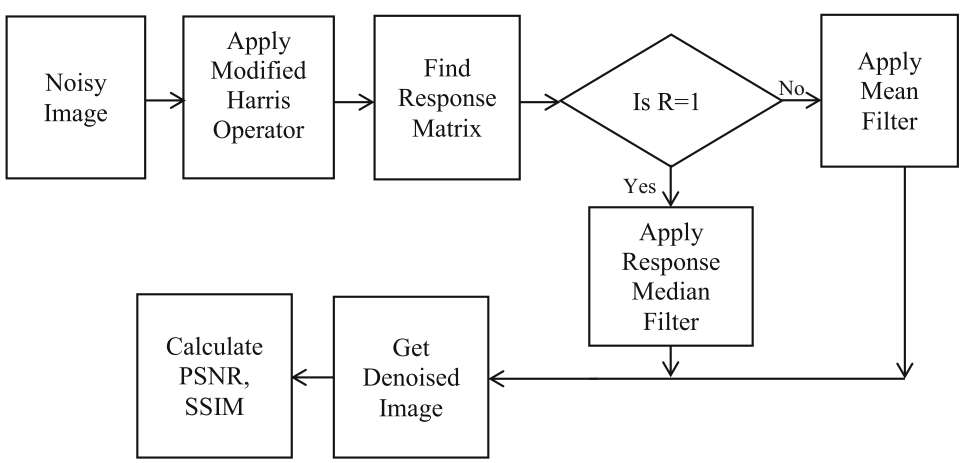


Figure 7. Block diagram of proposed work.

Table 2. PSNR comparison of proposed work with existing state-of-the-art algorithm.

	PSNR in dB					
Image	Noisy	MA	Median	Proposed method	NLM(P)	BM3D(P)
Spine	27.43	30.13	33.58	33.73	34.17	35.24
Hand	29.45	28.02	35.16	36.11	36.98	39.90
Dental	28.01	30.95	35.24	36.40	37.36	40.25
Knee	27.87	27.89	34.08	34.14	34.57	36.24
Chest	26.55	28.94	31.99	32.19	34.68	35.96

Table 3. Execution time comparison.

	Time required to get denoised image in seconds				
Image	MA	Median	Proposed method	NLM(P)	BM3D(P)
Spine	0.31	3.67	4.59	29.21	6.42
Hand	0.24	3.65	4.39	29.97	6.62
Dental	0.30	3.75	4.48	29.33	5.90
Knee	0.29	3.90	4.50	29.88	6.22
Chest	0.31	3.74	4.42	29.41	7.01

4. Result and discussions

The proposed method is implemented in MATLAB R2013a environment. Experimentation is performed on variety of X-ray images. Poisson noise is applied synthetically to create noisy X-ray input set. Proposed work is compared with basic median filter, moving average filter (MA), non-local means for Poisson reduction (NLM(P)) and Block Matching 3D collaborative filtering for Poisson (BM3D(P)) techniques. Table 2 shows a comparison of proposed algorithm with existing techniques with respect to quality metric peak signal to noise ratio (PSNR).

It is observed from table 2 that performance of proposed algorithm is better than simple median and MA filter with respect to PSNR. We also observed that performance is very close to the current state-of-the-art techniques like NLM(P) and BM3D(P).

Complexity of algorithm decides its execution time. Comparison of the proposed algorithm complexity with other techniques on the basis of execution time is done. This exercise is stated in table 3.

It is observed that the proposed algorithm has less time complexity as compared to NLM(P) and BM3D(P) algorithms. Median filter needs average 3.79 s, whereas the proposed technique need average 4.32 s. This difference is very less $\sim$0.5 s only.

Visual improvement is achieved over noisy images and quality of denoised image is acceptable. These visual results are displayed in figure 8.

In figure 8, original images, noisy images and denoised by the proposed method images are included. Sample results are shown for chest, knee, spine, hand and dental images. Similarly, results of the proposed algorithm are compared with median filter and there are very encouraging visible results. Figure 9 shows superiority of the proposed algorithm over median filter.

Dominance of proposed algorithm is also observed from following image matrix 1 and 2. Matrix 1 indicates difference between original image and median filtered image.

2	5	2	11	12	15	17	27	49	40	19	9	4	-9	-8	-4	4	-4	-8	18
18	17	17	16	12	13	21	42	47	17	7	4	-2	7	20	6	7	2	-3	7
12	16	19	7	7	20	45	58	28	7	6	18	12	12	9	14	6	3	-6	-7
20	6	7	22	28	60	48	25	5	19	12	19	19	10	7	16	19	13	-3	-8
10	24	48	47	59	51	18	-10	-6	4	1	6	19	20	18	13	4	13	7	-1
34	61	39	23	14	-5	-6	-4	7	2	11	6	18	26	22	13	5	12	5	1
66	42	10	-2	0	-6	3	10	5	5	19	20	12	18	15	10	3	4	1	10
9	-5	1	-5	8	9	18	26	6	14	13	6	10	14	7	4	-11	14	5	6
-2	-5	4	9	19	17	14	11	16	3	4	1	9	15	10	6	-4	8	9	18
5	9	15	7	13	19	20	6	1	-2	-2	-5	1	3	7	12	13	21	16	8

Similarly, difference between original image and proposed algorithm is depicted in matrix 2.

1	4	1	11	14	12	14	23	45	43	26	12	10	10	10	8	17	15	16	51
19	17	14	12	11	13	18	37	39	26	1	-8	-17	-8	0	16	18	22	1	24
14	15	11	15	0	19	48	50	26	-4	0	6	-1	8	8	26	13	12	13	8
14	9	5	17	29	50	48	20	7	6	0	6	9	9	10	17	25	11	0	3
12	23	43	46	51	43	19	-13	-1	0	0	5	23	31	22	21	8	23	13	11
35	49	48	38	28	5	-9	-12	3	6	15	17	24	40	22	5	0	25	17	9
52	40	25	11	13	1	0	8	15	22	24	24	20	19	7	-1	8	15	1	9
30	19	1	-1	0	2	1	21	12	21	21	14	16	18	15	-8	-7	11	8	8
9	8	3	8	17	15	14	15	20	17	21	8	10	24	14	10	0	-2	10	12
7	5	11	19	10	22	23	26	24	20	7	1	9	3	1	7	10	17	17	8

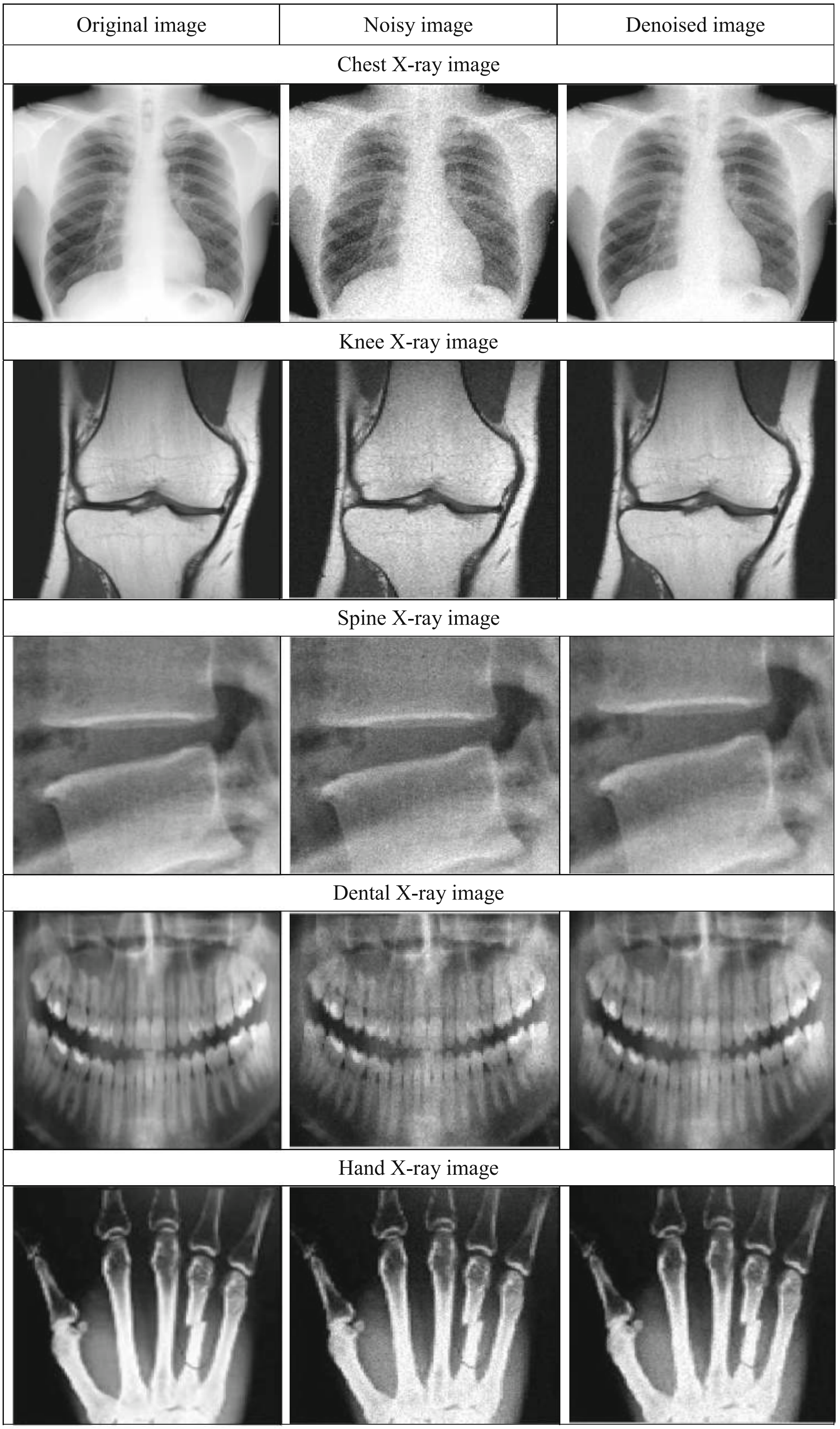


Figure 8. Visual results of proposed algorithm.

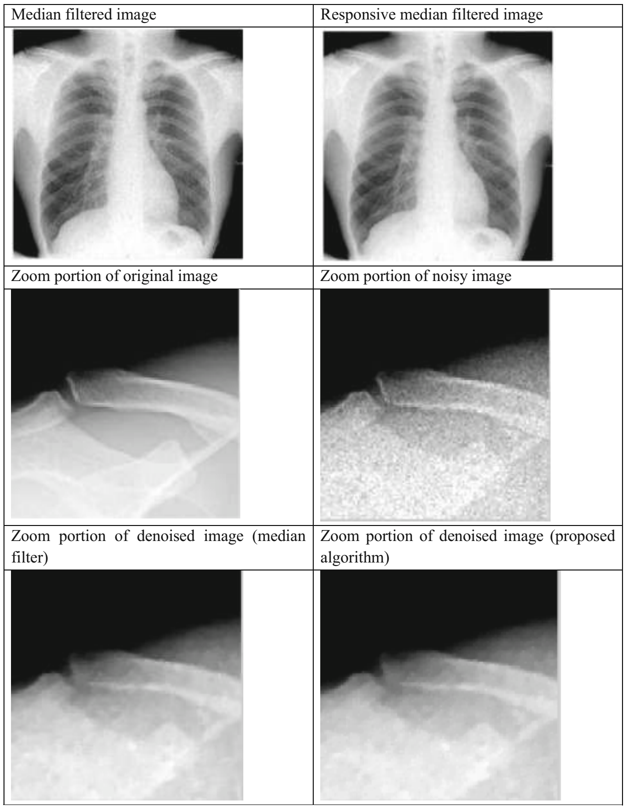


Figure 9. Detailed comparison of median and proposed algorithm.

In above image matrices 1 and 2, blue-coloured box indicates locations for which difference between original image, median filtered image and proposed responsive median filtered image has 0 or 1 value. It is also observed that the proposed algorithm performs better than median filter with respect to visible quality of image. Superiority of the proposed algorithm is mainly due to selective processing of pixels. In case of median filtering, each and every pixel is processed, though it is not noisy. Hence, alteration of noise-free pixel reduces X-ray image quality.

Figure 10 shows a comparison of the proposed algorithm against techniques like wavelet domain thresholding, DTCW transform and thresholding, curvelet transform and thresholding proposed for Poisson noise reduction. Significant amount of improvement is achieved in performance measures, PSNR and visual appearance.

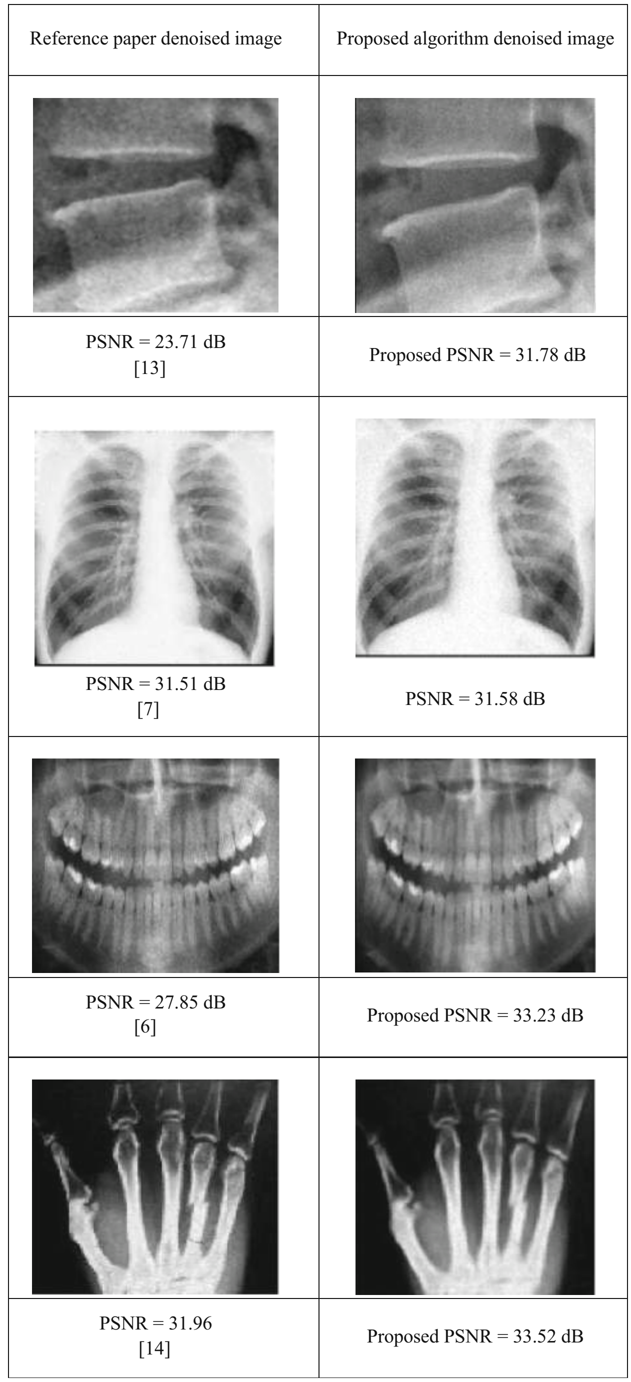


Figure 10. Comparison with other algorithms.

5. Conclusions and future scope

In this paper, new spatial domain approach is proposed in which use of Harris corner detector is introduced with slight modifications. This method has been proved successful for prediction of noisy and noise-free pixels and classification of region of interest and region of non-interest according to response matrix. Experimentation can be concluded as region classification and responsive median filtering is simple but most effective technique to remove Poisson noise from X-ray images. This is proved by our experimentation and comparison with the state-of-the-art methods. The proposed technique need less execution time compared to non-local means for Poisson and Block matching 3D collaborative filtering technique and also gives encouraging visible results. Proposed algorithm is able to give improved PSNR over wavelet, dual tree complex wavelet transform and Curvelet transform. By region classification, we claim that our algorithm reduces the operation overhead.

Extension of proposed work is possible for accuracy improvement of prediction mechanism and use of some improved filtering technique.

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