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Edge Preserved De-noising Method using Bilateral Filter for X-ray and GIS Images

Rajitha Bakthula[1], Suneeta Agarwal[2] and Apurva Mithal[3]

[1,2,3]*MNNIT Allahabad, Uttar Pradesh, India*

Abstract—*GIS and Medical X-ray images refer to the images captured by the satellites and specialized electronic devices. GIS images are used to survey and analyze the satellite-range prone regions and extract useful information like two and three-dimensional characteristics of the Earth's surface, subsurface, atmosphere etc contained in the regions. Medical X-ray images are used to analyze the human internal bone structure for fracture/diseases identification for better diagnosis. However, during the process of acquisition and transmission of these images, noise may be introduced to them or image may be corrupted with noise during acquisition. Due to which the analysis might become tedious. Thus any de-noise method should preserve the edges while de-noising. This paper proposes an ideal method using a NeighShrink SURE based de- noising algorithm and a bilateral filter with the primary aim to preserve the edge information. The proposed algorithm is compared with median, visushirnk, normalshrink and bayeshink method and given better results for proposed method with higher SNR and PSNR values. The edge preservation was the main focus in this paper hence the Accuracy and Error Rate are also measured for original edges.*

Keywords*: Image de-noising, discrete wavelet transform, thresholding, additive white Gaussian noise, bilateral filter, NeighShrink SURE, 2d-median, Bayes Shrink, Normal Shrink, VisuShrink, Kirsch operator, confusion matrix.*

1. INTRODUCTION

De-noising is one of the most complicated yet essential and desired task in image processing. Noise produces an undesired effect in the image. Different de-noising algorithms have been proposed and implemented in the past to deal with the different types of noises. Image noise can be classified as Impulse noise (Salt-and-pepper noise), Amplifier noise (Gaussian noise), Shot noise, Quantization noise (uniform noise), Film grain, on-isotropic noise, Multiplicative noise (Speckle noise) and Periodic noise. In this paper we will concentrate on the additive white Gaussian noise (AWGN).

No image is totally free of noise. All imaging devices procedures of some type of noise. But noise is more significant and prevalent in certain types of imaging devices than others. Noise is extremely significant in case of GIS and X-Ray images. This paper is aimed to reduce white Gaussian noise present in the these images. Gaussian noise is a statistical noise where probability density function (PDF) equals that of normal distribution also known as Gaussian distribution. White Gaussian noise is a special case where the values at any pair of times are statistically independent and identically distributed. Conventional Gaussian noise removal techniques include mean filtering, median filtering, Gaussian smoothing.

One of the noise artifacts created by de-noising is the attenuation of the high spatial frequencies which may result in the smoothening of the edges in the image. This smoothening of the images is referred to as the blurring effect. Image De-noising may result in the loss of useful information from the image. Edge features are an important component of image under study because they represent the major characteristics of the image objects and are easier to capture our visual attention. Therefore, edges should be well preserved during image de-noising. Therefore, the objective of the paper is to innovate a simple, yet effective algorithm for the removal of the noise present in the X-ray and GIS images while preserving its edges with essential details. For the above purpose, bilateral filter was applied to the de-noised reconstructed image. Further sections of this paper are discusses about the previous work done by several researchers for de-noising the X-ray and GIS images having Gaussian noise and later a detail on proposed work and the experimental results followed by a conclusion.

2. LITERATURE SURVEY

An ideal spatial adaptive wavelet shrinkage method was proposed by Donoho and Johnstone [1]. A new principle known as selective wavelet reconstruction was described by the authors. Later they also developed a spatially adaptive method known as Sure Shrink[2]. It worked on the principle of shrinkage of empirical wavelet coefficients. Chang and Vetterli [3] proposed an adaptive, data-driven thresholding technique based on wavelet soft thresholding. The threshold obtained is adaptive to each detail sub-band. This method is now widely known as Bayes Shrink.Zhuang and Baras [4] analyzed the problem of choosing an customized wavelet based on image with support for image data compression and thus provided an algorithm for computing the optimal wavelet basis. Normal Shrink method [5] which is a data driven and sub-band dependent thresholding technique. An optimal threshold value is calculated for each sub-band using the length of the sub-band and total number of decompositions. Sendur and Selesnick [6] proposed BiShrink method which uses the bivariate shrinkage function for thresholding. A probabilistic shrinkage based method known as ProbShrink was proposed by Pizurica and Philips [7]. It works by estimating the probability that a given coefficient contains a significant noise-free component and thereafter multiplying the wavelet coefficient with the probability calculated.

X-ray imaging modality is prone to noise because of thermal instability of many unified electronic components used in X-ray generators and detectors during acquisition process. X-ray images may be severely corrupted with Gaussian noise also known as AGWN (Additive Gaussian White Noise). It is an additive noise, which is consistently spread over the entire image. B. Hong et al. has proposed a method using Regularized P-M Diffusion in wavelet domain [8]. A method called Wavelet Embedded Anisotropic Diffusion (WEAD) was proposed by J. Rajan et al.[9]. Here the P-M method is applied at every detail coefficients of Wavelet sub-bands (HL-horizontal, LH-vertical and HH-diagonal). They have used soft thresholding by minimising the Bayesian Risk. The Bayesian Shrinkage has been applied over nonlinearly diffused signals. It has been observed that the performance of these two algorithms is good but can further increased.

3. PROPOSED ALGORITHM

Generally any de-noising algorithm includes decomposition of the noisy image into its low and high frequency components. Discrete Wavelet Transform (DWT) are very popularly used in this regard. The noisy image is decomposed into a single approximation sub-band which represents the low frequency components in the image and three detail sub-bands (Horizontal, Vertical and Diagonal) which represents high frequency components. The next levels of wavelet transform is applied only to the low frequency component i.e. approximation sub-band. Later a thresholding technique is applied based on the type of noise present in the image and the application in which the image is to be used. In this paper we have used NeighShrink SURE thresholding method. Using this method we can determine the optimal threshold value for each detail sub-band by Stein's unbiased risk estimate (SURE) [10]. Once the thesholding is done for all the detail sub-bands, the de-noised image is reconstructed using 2D- Inverse Discrete Wavelet Transform (2D-IDWT).

A) Proposed Algorithm Steps

1. Read the original noisy X-Ray or GIS image.
2. Convert to Gray-Scale image.
3. Decompose the noisy image using 2D-DWT to obtain the approximation and detail sub-bands.
4. Apply NeighShrink SURE algorithm to each detailed wavelet co-efficient to de-noise the noisy wavelet coefficients.
5. Reconstruct the modified coefficients using IDWT.
6. Apply the bilateral filter to the reconstructed de-noised image.

B) Discrete Wavelet Transform

Discrete Wavelet Transform is one of the wavelet transforms which involves discrete sampling of the wavelets. Its advantage over Fourier Transform is its ability to capture both frequency as well as location (in time) information. Since image is a two dimensional signal, 2-D DWT is applied to the image. The original image is passed through the high pass filter which results in three images, each describing local changes in brightness in the original image. These images are also known as detail sub-bands. They represent high frequency information present in the original image. It is then filtered and downscaled, yielding an approximation image. The approximation coefficients contain low frequency information present in the original image. This completes first level 2D-DWT. For second level 2D-DWT, the approximation image yielded from previous level is further decomposed for low and high frequency components.

C) NeighShrink SURE Thresholding

After the decomposition of the noisy image into approximation and detail coefficients, the next main task in the path of image de-noising is to find the appropriate thresholding method and the optimal threshold value for each of the detail sub-band. In this paper NeighShrink SURE method is adopted as the thresholding technique to de-noise the detail coefficients.

The steps to be performed before the implementation of Neigh Shrink SURE method are:

1. Extract approximation and detail coefficients obtained from 2D- DWT.
2. Calculate the median of absolute deviation (MAD)[10], [11] using the diagonal detail coefficients obtained from first level 2D-DWT by the following formula -

   $\widehat{\sigma}$=median($|w_s|$)/0.6745 (1)

   where $w_s \in$ diagonal detail sub-band obtained from first level 2D-DWT.
3. For non-unit noise variance, standardize all the detail and approximation coefficients by dividing the coefficients with $\hat{\sigma}$. Now we have a new set of standardized coefficients.
4. For each noisy wavelet coefficient w_{ij} that needs to be shrinked, a square neighboring window B_{ij} of size 3 * 3 centered at noisy wavelet coefficient is incorporated.
5. Then summation of the square of each pixel incorporated by the neighboring window is calculated.

$$S_{ij}^2 = \sum_{kl \in B_{ij}} w_{kl}^2 \quad (2)$$

This results in a new matrix of size same as that of the detail sub-band under consideration. Each pixel value of this new matrix is equal to S_{ij}^2 corresponding to each w_{ij}.

6. A threshold vector [9] is defined as
   $T = (R + 1): 0.1 : ((R + 1) * 3)$ (3)

where T is the threshold vector and R is the padding done (since neighboring window size is 3 therefore padding done R= 1.

7. For each threshold value in the threshold vector, unbiased estimate of the risk on the sub-band is calculated using Stein's unbiased risk estimate (SURE). Thus, for the detail sub-band under consideration, we obtain a SURE vector of size similar to that of the threshold vector.
8. Then the threshold value from the threshold vector at which SURE minimizes is found and is termed as the optimal threshold value for that sub-band.
9. The shrinkage factor for each pixel of the sub-band is calculated by using the optimal threshold value for that sub-band and S_{ij}^2.
   β_{ij}=max((1$-optimal_{thresh}{}^2/S_{ij}^2$),0) (4)
10. The NeighShrink shrinkage wavelet coefficient is obtained by

$$\widehat{\theta_{ij}} = w_{ij} * \beta_{ij} \quad (5)$$

where $\widehat{\theta_{ij}}$ is estimator of the unknown noiseless coefficient, w_{ij} is the noisy coefficient of the detail sub-band to be shrinked and β_{ij} is the corresponding shrinkage factor for that noisy wavelet coefficient.

D) Inverse DWT

After thresholding all the detail sub-bands by NeighShrink SURE technique, the modified coefficients are reconstructed using two dimensional Inverse Discrete Wavelet Transform (2D-IDWT). Once the de-noised reconstructed image is obtained, the reconstructed image matrix is multiplied with $\hat{\sigma}$ (since we initially standardized the coefficients).

E) Bilateral Filter

A bilateral filter [12] is a smoothing filter that performs smoothening of an image non-linearly with edge preservation. It replaces the intensity value of centered pixel by a weighted average of intensity values of neighboring pixels in an image. It is applied to the de-noised image to remedy the blurring effect caused by thresholding technique. Input to the bilateral filter is the de-noised reconstructed image. Steps to be performed are:

1. Define a neighboring window of size 5*5.
2. Consider a pixel of the reconstructed de-noised image located at (i, j) and one of its neighboring pixels located at (k, l). Then, the weight assigned to the neighboring pixel at
   (k, l) is given by

$$w(i,j,k,l) = e^{\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2} - \frac{||I(i,j)-I(k,l)||^2}{2\sigma_r^2}\right)} \quad (6)$$

where σ_d and σ_r are smoothing parameters and I(i, j) and I(k, l) are the intensity of pixels at (i, j) and (k. l) locations respectively.

3. The new intensity value for the pixel at location (i, j) is given by

$$I_D(i,j) = \frac{\sum_{k,l} I(k,l) * w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)} \quad (7)$$

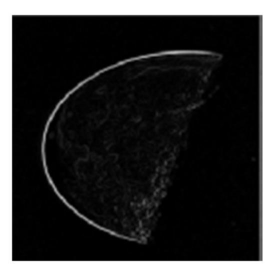
F) Canny Edge Detection Operator

Canny edge operator is a multi-stage algorithm to detect the edges from the image. It was proposed by John F. Canny in 1986 [13]. Canny algorithm main focus is to detect every minute edge in the image by neglecting lower level noise terms. Canny is proven to be better edge detection approaches. It was implemented to measure the performance of the proposed algorithm in terms of edge preservation. Canny operator was applied to the original noiseless image and the de-noised image obtained after applying 2D Median, Normal Shrink, Bayes Shrink, Visu Shrink and Proposed Bilateral filter results. The resultant images of de-noised methods are compared with the original image edges for measuring the Accuracy of true edges are detected as truly and false edges are detected falsely.

4. EXPERIMENTAL RESULTS

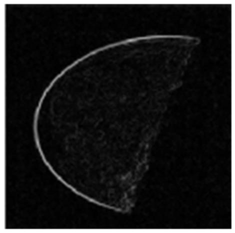
Noisy images of X-ray and GIS images are denoised using the proposed method. For comparison the 2d-median, Visu Shrink, Bayes Shrink and Normal Shrink method are implemented. Fig. 1 and Fig. 2 illustrates the de-noised resultant images on GIS and X-Ray images by applying proposed and

(a) Noisy image



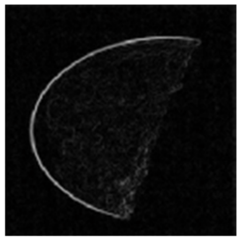
(b) Original Edges

(c) 2D Median Resultant Image



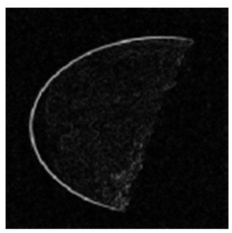
(d) 2D Median Resultant Image Edges

(e) Visu Shrink Resultant Image



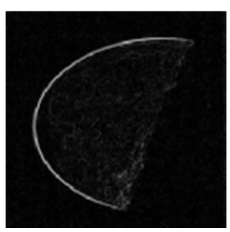
(f) Visu Shrink Resultant Image Edges

(g) Bayes Shrink Resultant Image



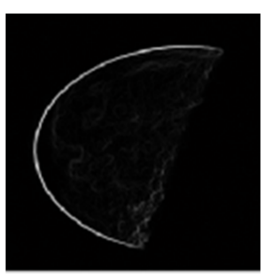
(h) Bayes Shrink Resultant Image Edges

(i) Normal Shrink Resultant Image



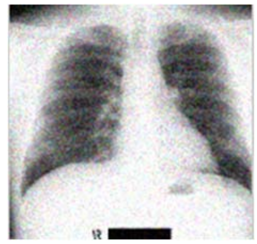
(j) Normal Shrink Resultant Image Edges

(k) Proposed Resultant Image



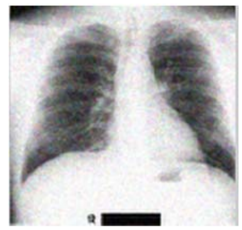
(l) Proposed Resultant Image Edges

Fig. 1: Original noisy image and its de-noised images using 2d-median, VisuShrink, Bayes Shrink, Normal Shrink and Proposed method. Here edges are detected using Kirsch operator.



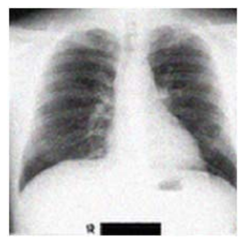
(a) Noisy image

(b) Original Edges



(c) 2D Median Resultant Image

(d) 2D Median Resultant Image Edges

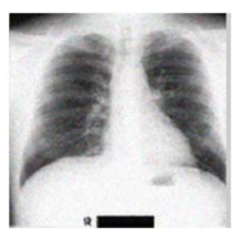


(e) Visu Shrink Resultant Image

(f) Visu Shrink Resultant Image Edges

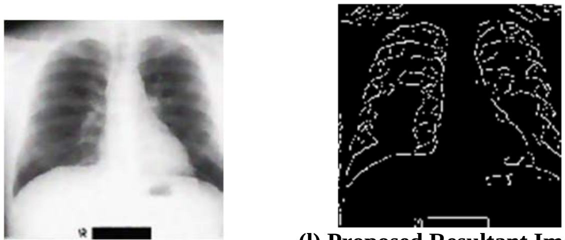
(g) Bayes Shrink Resultant Image

(h) Bayes Shrink Resultant Image Edges



(i) Normal Shrink Resultant Image

(j) Normal Shrink Resultant Image Edges



(k) Proposed Resultant Image **(l) Proposed Resultant Image Edges**

Fig. 2: Original noisy X-Ray image and its de-noised images using 2d-median, VisuShrink, Bayes Shrink, Normal Shrink and Proposed method. Here edges are detected using Kirsch operator.

comparison methods. Performance of the proposed and comparison methods are compared using very popular measures PSNR and SNR [14, 15] as stated in Eq. (8) and (9). These metrics demonstrates the level of noise reduction from the image. Table 1 tabulates the values of SNR and PSNR for the test image. Here proposed method has shown the better SNR and PSNR values in comparison to other methods. Edges accuracy for better de-noising is measured using the performance metrics Accuracy, and Error Rate [16] shown in Eq.(10) to Eq.(11). Here N_{TN}: Number of True Negative, N_{TP}: Number of True Positive, N_{FP}: Number of False Positive, N_{FN}: Number of False Negative respectively.

Analyzing the Fig. 1 and 2 it is observed that the noisy pixels are reduced in all the de-noising methods but, the level of original edges preservation is not retained in all methods. Fig. 1 (b, d, f, h, j, l) and Fig. 2(b, d, f, h, j, l) are depicting the edges of de-noised method using canny edge detector. These Fig. show that most of the edges are not preserved or retained in normal shrink, bayes shrink, visu shrink and 2dmedian methods. But, the proposed method has performed better in removing the noise as well as preserving the edges. Hence to measure these results a mathematical analysis is done on the results of all methods using SNR, PSNR and Accuracy in Table 1 and Table 2. On studying these tables it is observed that the proposed method has shown the better results in comparison other methods with higher SNR and PSNR Values in both GIS and X-ray images (in Table 1 & Table 2). The Accuracy is measured to verify the edge preservation of de-noised image to original noise free image. Here as well the proposed method has shown the improvement in accuracy percentage values.

$$SNR = 10.log_{10}\left[\frac{\sum_0^{n_x-1}\sum_0^{n_y-1}[r(x,y)]^2}{\sum_0^{n_x-1}\sum_0^{n_y-1}[r(x,y)-t(x,y)]^2}\right] \quad (8)$$

$$PSNR = 10.log_{10}\left[\frac{\max(r(x,y))^2}{\frac{1}{n_x.n_y}\sum_0^{n_x-1}\sum_0^{n_y-1}[r(x,y)-t(x,y)]^2}\right] \quad (9)$$

where $r(x,y)$ is the reference image i.e. original noiseless image, $t(x,y)$ is the test image i.e. de-noised image, n_x is the number of rows and n_y is the number of columns in the de-noised image which is same as that in original noiseless image.

$$Error\ Rate = \frac{N_{FP}+N_{FN}}{N_{TN}+N_{FN}+N_{TN}+N_{FP}} \quad (10)$$

$$Accuracy\ = 1 - Error\ Rate \quad (11)$$

Table 3 tabulates the average values of SNR, PSNR and Accuracy for 2dmedain, visu shrink, Bayes Shrink, Normal Shrink and Proposed methods by considering the dataset images. Here a total of 100 images are studied comprising GIS and X-ray images. Analyzing these performances it is observed that 2D Median method hand 20.73, 21.81 and 76% of SNR, PSNR and Accuracy measures, which are very low in compared to other methods. In our study VisuShrink, BayesShrink and Normal Shrink methods has shown almost the same measures. In contrast proposed method had a higher rate of accuracy with 82% for edges preservation including the 26.81 and 27.89 SNR and PSNR values. Hence the proposed method is better in comparison to other methods.

Table 1: Performance Measures by considering the GIS image (gis1 with noise variance = 0.01).

Method	SNR	PSNR	Accuracy (%)
2D-Median	18.24	21.48	84.43
Visu Shrink	20.10	23.34	84.04
Bayes Shrink	20.08	23.32	84.14
Normal Shrink	20.51	23.76	84.12
Proposed	23.52	26.76	85.23

Table 2: Performance Measures by considering the X-Ray image (with noise variance = 0.01).

Method	SNR	PSNR	Accuracy(%)
2D-Median	24.62	22.15	81.21
Visu Shrink	26.28	23.81	81.63
Bayes Shrink	26.40	23.93	81.91
Normal Shrink	26.27	23.80	81.64
Proposed	30.39	27.92	84.66

Table 3: Average Performance Measures of Dataset Images (100)

Method	SNR	PSNR	Accuracy(%)
2D Median	20.73	21.81	76
Visu Shrink	22.31	23.39	78
Bayes Shrink	22.32	23.4	78
Normal Shrink	22.26	23.39	78
Proposed	26.81	27.89	82

5. CONCLUSION

De-noising images is an crucial task in image processing since better analysis and diagnosis directly depends on quality of the image. Quality of an image depends on the clarity of the image both in low and high level coefficients. Thus this paper presents an approach for de-noising the GIS and X-Ray images by preserving the edges and smoothening the non-edge locations of the image. The proposed method works first by decomposing the image using DWT, thresholding each detail co-efficient with NeighShrink SURE method and finally applying the Bilateral Filter for noise reduction. Here the proposed method is compared with other thresholding algorithms namely 2d-median, Visu Shrink, Bayes Shrink and Normal Shrink. The proposed algorithm has found the optimal threshold value for each wavelet sub-band separately instead of using an universal threshold value. Proposed algorithm also produced higher SNR, PSNR and Accuracy values of 26.81, 27.89 and 82% in average by considering 100 images. Hence its proved that the edges are been preserved using the proposed method.

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