Analysis of the Application of Bi-Orthogonal Wavelet Transform, Bayesthresholding and Independent Component Analysis (ICA) on Poisson Noise Removal from X-Ray Images

N. Umadevi and Dr.S.N. Geethalakshmi

Abstract---Medical field produces huge volume of images, which are used during disease diagnosis. X-Rays are the oldest and most frequently used form of medical imaging. These images are used in many applications with prominent use found in fracture detection. The X-Ray images are normally affected by Poisson noise, which degrades the visual quality of the image and obscures important information required for accurate diagnosis. The current need is, thus, a method that removes noise while preserving important diagnostic data. This study proposed a method that combines Multiple Wavelet Denoising (MWD) Structure with ICA to remove Poisson noise from X-Ray images. The thresholding method used is BayesShrink and both soft, hard thresholding methods are analyzed. From the experimental results, it is evident that the proposed model produces images, which are visually clean and smooth, in fast manner. At the same time, the proposed method also preserves edges and other significant details of the image.

Keywords---Multiple Wavelet Denoising (MWD), Bi-Orthogonal Wavelet Transform, Bayesthresholding and Independent Component Analysis (ICA), Poisson Noise.

I. Introduction

THE rapid development in medical research produces a continuous stream of new knowledge about disease processes, new therapeutic targets and the complex relationship between a person's genome and his/her related risk for disease. Medical imaging now plays a central role in the global healthcare system as it contributes to improved patient care. Medical imaging covers many different imaging modalities: X-Ray-based methods such as radiography and Computed Tomography (CT), Magnetic Resonance Imaging (MRI), ultrasound (US), nuclear medicine with Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT), and several methods in optical imaging. The main problem encountered by medical imaging systems is the distortion of visual signals obtained due to imperfect acquisition and transmission errors. These distortions are termed as 'Noise' an have to be removed to improve the quality of the image. The techniques used to remove noise are termed as "Image Denoising". Image denoising, a well-studied problem in computer vision for natural images, is still in infantry stage where medical imaging is concerned. It is the most sought after tool by the image analysts in the fast-growing medical field, as noisy images often lead to incorrect diagnosis.

The main objective of image denoising techniques is to remove noises introduced during acquisition and transmission, while retaining as much as possible the important signal features (Sudha et al., 2009). Denoising techniques is considered a challenging research area because of two reasons. The first is that the process of denoising is irreversible and therefore, one has to be very careful while removing noise regions, in order to avoid removing important regions. For example, a tumour presence should not be considered as noise.

In this paper, the noise in X-Ray images is considered. An X-Ray (radiograph) is a noninvasive medical test that helps physicians diagnose and treat medical conditions. Imaging with X-Rays involves exposing a part of the body to a small dose of ionizing radiation to produce pictures of the inside of the body. X-Rays are the oldest and most frequently used form of medical imaging. Different parts of the body absorb the X-Rays in varying degrees. Dense bone absorbs much of the radiation while soft tissue, such as muscle, fat and organs, allow more of the X-Rays to pass through them. As a result, bones appear white on the X-Ray, soft tissue shows up in shades of gray and air appears black. Until recently, X-Ray images were maintained as hard film copy (much like a photographic negative). Today, most images are digital files that are stored electronically. These stored images are easily accessible and are frequently compared to current X-Ray images for diagnosis and disease management.

The generated X-Rays may be scattered in time and space because of a non-continuous arrival at the receiving system. Because the X-Ray scattering follows a Poisson distribution, such images are known as images with Poisson noise added (Wang *et al.*, 2008). They also suffer from low / high contrast. In applications like fracture detection, a preprocessing step is included to adjust contrast and reduce Poisson noise (Sakata and Ogawa, 2009).

In the past, many filters like, median, Wiener, nonlinear filters and other optimization filters have been used as restoration methods for images with noise. A median filter is a filter effective for both preserving the edges that cannot be

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preserved in a conventional linear filter and removing the impulse noise. Media filter, though effective at reducing noise has a blurring effect which reduces the difference between edge and non-edge region of the image. The Wiener filter is a filter that is more effective at preserving image edges and higher frequency areas than a conventional linear filter (Tsukahara *et al.*, 1998). However, the result is often too blurred. In recent years, noise elimination methods using a wavelet transform have been gaining attention (Niijima, 2000). Wavelet based denoising involves threshold processing for each wavelet region, which identifies noise dominant regions. Noise elimination techniques are then used in noise dominant regions and signal preservation techniques are used in regions where the original signal component is dominant. However, although threshold processing methods for the wavelet region are effective for images with Gaussian noise, the performance is not very effective with a medical X-Ray image.

Luisier *et al.* (2010) proposed a fast interscale wavelet denoising method for Poisson-corrupted images. This model is referred to as 'Base Model' in this paper. They used Haar wavelet transformation with soft thresholding and introduced a method called PURESHRINK to reduce Poisson noise in an image. This method had the advantage that while performing efficient Poisson denoising in a time efficient manner, in some cases, it introduced 'staircase' artifacts. In this paper, the base paper is enhanced by using a decimated biorthogonal Haar (Bi-Haar) transform (Zhang *et al.*, 2008) and then use Independent Component Analysis (ICA) (Marusic *et al.*, 2005) to remove dependencies between the data streams associated with each wavelet decomposition. The threshold function used is changed to BayesThreshold. Both soft and hard thresholding methods are also explored. Further, a method to adjust the contrast of an image is also used to improve the quality of the X-Ray images, which can then be used for efficient fracture detection.

The paper is organized as below. Section 2 presents the denoising system while using wavelets. Section 3 discusses ICA based denoising method. Section 4 explains the proposed method for removing Poisson noise from X-Ray images. The results obtained during experimentation are presented and discussed in Section 4. Section 5 concludes the work.

II. Wavelet Based Denoising Model

Wavelet approach for noise removal has been successfully exploited by several researchers (Kaur and Singh, 2010; Federico and Kaufmann, 2007; Delakis *et al.*, 2007) in the past few decades. It has been proved that the use of wavelets successfully removes noise while preserving the signal characteristics, regardless of its frequency content. A wavelet denoising model can be represented by the Equation 3.

$$I(t) = O(t) + N(t) \qquad (1)$$

where O(t) represents the original noise free data, N(t) is the Poisson noise. Let W(f) and $W_i'(f)$ denote the forward and inverse wavelet transform operators. Let D(f, λ) denote the denoise operator with threshold λ. The main aim of the denoising procedure is to denoise I(t) to recover O'(t). The general wavelet model is shown in Figure 1. This model consists of three main steps after image acquisition. The first step is a linear forward Discrete Wavelet Transform (DWT), followed by a non-linear thresholding step and the final step performs a linear Inverse Discrete Wavelet Transform(IDWT).

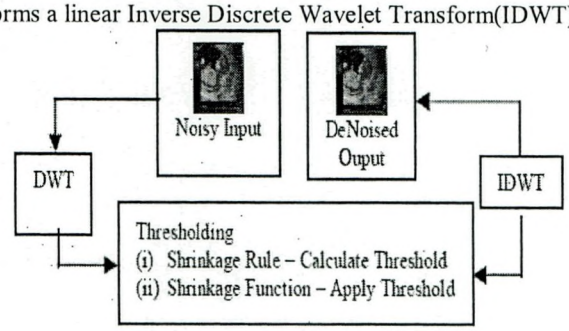


Figure 1 : Wavelet Model

A. *Discrete Wavelet Transform (DWT)*

The first step is the selection of the forward and inverse wavelet transformation. A variety of wavelets transformation techniques are available for the purpose of denoising. Some of them include Haar, Daubeschies, Coiflets, Symlets, Morlets, Mexican Hat, Meyer and Biorthogonal wavelets (Ibrahim *et al.*, 2007). The present study considers Haar, Daubeschies and Coiflets into consideration for denoising. Application of DWT divides an image into four subbands (Figure 2), which arise from separable applications of vertical and horizontal coefficients. The LH, HL and HH subbands represents detailed features of the images, while LL subband represents the approximation of the image. To obtain the next coarse level, the LL subband can further be decomposed (Figure 2b), thus resulting in the 2-level wavelet decomposition. The level of decomposition performed is application dependent. The present work considers upto four level of decomposition. The advantages of using wavelets for denoising are multifolded. The first is that different sized images at different resolution can be analyzed, the coefficients are small in magnitude and the large coefficients coincide with image edges. The edge coefficients within each subband tend to form spatially connected clusters.

B. *Thresholding*

The second step is the selection of a wavelet thresholding technique. Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising. It removes noise by killing or shrinking coefficients that are insignificant relative to some threshold. They are simple yet effective and depend heavily on the thresholding parameter. The efficiency of wavelet model greatly depends on the correct choice of parameter. Wavelet thresholding is composed of two steps namely, thresholding method and threshold selection.

1) Threshold operators

Most frequently used thresholding methods are soft and hard thresholding. The hard and soft thresholding operations are defined as in Equations (4) and (5).

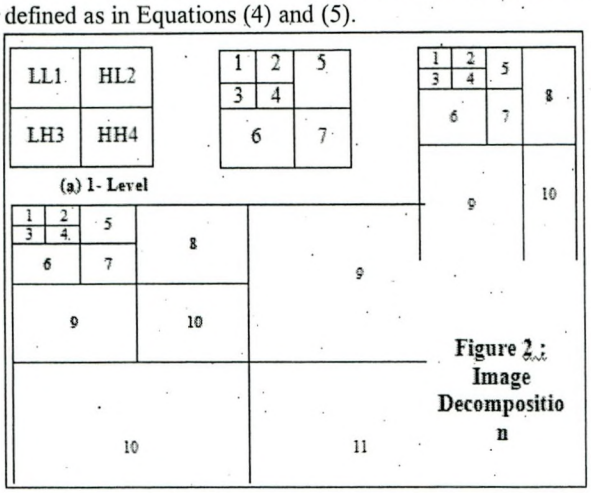
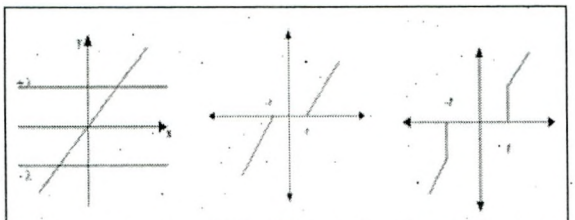


Figure 2 : Image Decomposition

$$T_{hard}(I,\lambda) = \begin{cases} I & \text{for all } |I| > \lambda \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

$$T_{soft}(I,\lambda) = \begin{cases} \text{sign}(I)\max(0,|I|-\lambda & \text{for all } |I| > \lambda \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

The hard threshold work on the "Kill or Keep" principle where the input is kept, if it is greater than a defined threshold (λ) otherwise it is set to zero. It removes noise by thresholding only the detailed subband wavelet coefficients, while keeping the low-resolution coefficients unaltered. An extension to hard thresholding is the soft thresholding, which works on the "Shrink or Keep" principle. The output is forced to zero, if the absolute value of I is less than the threshold λ else the output is set to $|I-\lambda|$. The effect of hard and soft thresholding on an original signal is given in Figures 3a,b,c. Discontinuities at $\pm\lambda$ is seen with hard thresholding and they are more sensitive to small changes, while soft threshold avoids both these situations. Thus the advantages of soft thresholding are it reduces abrupt sharp changes and provides an image whose quality is not degraded. Because of these advantages, soft thresholding is more frequently used. Once the thresholding operator has been defined, the next step is to address the problem of selecting the corresponding threshold.



(a) Original Signal (b) Hard Threshold (c) Soft Threshold

Figure 3 : Effect of Thresholding

2) Selection of threshold

The selection of threshold is the most important step in any wavelet based denoising model. Careful selection is needed because a small threshold will produce an image which is still noisy, while a large threshold destroys details and produces blurs and artifacts. Two types of thresholding techniques, namely, Universal Thresholding (UT) and Subband Adaptive Thresholding (SA) exists. UT was proposed by Donoho and Johnstone in 1995 where the threshold λ is calculating as in Equation 6.

$$\lambda = \sigma\sqrt{2\log(M)} \quad 6(3)$$

where σ is the local noise variance in each subband of the Poisson image after decomposition and M is the block size in the wavelet domain. The estimated noise variance in each subband is obtained by finding the average of squares of the wavelet coefficients at the highest resolution scale (Equation 4)

$$\sigma = \frac{\sum_{i=0}^{N-1} (X_j)^2}{N} \quad 7(4)$$

The three famous threshold calculating techniques, namely, VisuShrink, SureShrink and BayesShrink. VisuShrink uses the universal thresholding, while SureShrink and BayesShrink uses data drive adaptive technique. The present method uses BayesShrink and is explained below.

The goal of BayesShrink method is to minimize the Bayesian risk, and hence its name, BayesShrink. It uses soft thresholding and is subband-dependent, which means that thresholding is done at each band of resolution in the wavelet decomposition. Like the SureShrink procedure, it is smoothness adaptive. The Bayes threshold, t_B, is defined as

$$t_B = \sigma^2/\sigma_s^2 \quad (8)$$

where σ^2 is the noise variance and σ_s^2 is the signal variance without noise. The noise variance σ^2 is estimated from the subband HH1 by the median-estimator. From the definition of additive noise,

$$w(x, y) = s(x, y) + n(x, y) \quad (9)$$

Since the noise and the signal are independent of each other, it can be stated that

$$\sigma^2_w = \sigma^2_s + \sigma^2_w \quad (10)$$

$\sigma^2 w$ can be computed using Equation (15). From this the variance of the signal, σ^2_s can be computed using Equation (12).

$$\sigma_w^2 = \frac{1}{n^2}\sum_{x,y=1}^{n} w^2(x,y) \quad (11)$$

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2, 0)} \quad (12)$$

with σ^2 and σ^2_s, the Bayes threshold is computed from Equation (8). In this paper, the Bayes threshold method is used.

III. ICA DENOISING MODEL

ICA based denoising method (Hyvarinen, 1999; Hyvarinen *et al.* 2000 and Hoyer, 1999) uses the fact that ICA components of many signals are often very sparse and can be used to remove noises. The algorithm first employs fixed-point algorithm on the noise-free data to get the ICA transformation matrix and then use maximum likelihood to estimate parameters for the shrinkage scheme. The method used by Hyvarinen *et* al. (2000) is explained below.

Assume an n-dimensional vector 'x' as x = s + v, where 's' is the vector of the original signal and 'v' is the noise. The goal of denoising is to find s' = g(x) such that v' is close to v in some well-defined sense (Zhang *et al.*, 2000).

Step 1 : Estimate the orthogonal ICA transformation matrix 'W' using a set of noise-free representative data 'z'.

Step 2 : For i = 1, ..., n, estimate a density model which approximates the actual distribution of the variable $s_i = w_i^T z$, where w_i is the ith column of W. Based on the estimated model and the variance of 'v', the non-linear shrinkage function g_i is calculated using step 3.

Step 3 : For each observed 'x',

1. ICA transform $y = Wx$
2. Non-linear shrinkage $s'_I = g_i(y_i)$
3. Reverse transform $s' = W^T s'$

Comparing with wavelet methods, ICA performs better as they use a transform which is estimated from the available data. But, they require additional noise-free data to train the denoising model and estimate the transformation matrix W and shrinkage non-linearities. In some applications, it might be difficult to obtained noise-free training data.

IV. PROPOSED DENOISING METHOD

The fundamental tool, in PURESHRINK method, is a statistical estimate of the Mean Square Error (MSE) between the (unknown) noiseless image and the processed noisy image. Owing to the Poisson noise hypothesis, this technique was named as Poisson Unbiased Risk Estimate (PURE) by its authors Luisier *et al.* (2010). The method uses a orthogonal Haar wavelet transform and uses a threshold, T, that is proportional to the square root of the scaling coefficient at the same location and scale. This quantity is an estimate of the local noise standard deviation, so that it is a good reference for assessing the significance of a wavelet coefficient. Indeed, each wavelet coefficient of the un- normalized Haar transform follows a Skellam distribution, whose variance is equal to the sum of the two underlying Poisson intensities, i.e., approximately the corresponding scaling coefficient. The PUREshrink estimator is defined as

$$\theta_n^{\text{PUREshrink}}(d,s;a) = \text{sign}(d_n)\max(|d_n| - a\sqrt{|S_n|},0) \quad (13)$$

where, for each wavelet subband, the parameter 'a' is set to the value that minimizes the PURE with $\theta(d, s)=\theta^{\text{PUREshrink}}(d, s; a)$. A soft thresholding approach is used that uses the concept of Linear Expansion of Thresholds (LET). According to this concept, the "acceptable" denoising processes are expressed as a linear combination of elementary denoising processes, from which only the wei unknown. It is these weights that are then comp minimizing the PURE, through the resolution of linear system of equations. This means that all the pa of the algorithm are adjusted completely auto without requiring user input. The advantage obtaine the thresholds are adapted to local estimates of th dependent) noise variance. These estimates are deri the corresponding low-pass coefficients at the same latter are also used to incorporate interscale relation the denoising functions. The resulting procedure can integrated into the wavelet decomposition, whic redundant. The MSE estimate is optimized indepen each subband by exploiting the orthogonality of wavelet basis. As a result, the algorithm computational complexity and modest memory req These are valuable features for denoising large dat as those typically produced in medical ap Importantly, this computational efficiency is not quality. On the contrary, the algorithm yields results.

The Haar wavelet used in this paper, the ortho wavelet framework of PURE is combined with a bi Haar wavelet transform. Haar wavelet provides a r distribution over wavelet coefficients. But due to continuity of Haar filters, its estimate can be high with strong "staircase" artifacts when decimation i To solve this dilemma between distribution manag reconstruction regularity, the use of Bi-Haar proposed. Its implementation filter bank is given by

$$h = 2^{-c}[1,1] \qquad g = 2^{-c} r\left[\frac{1}{8},\frac{1}{8},-1,1,-\frac{1}{8},\right.$$

$$\tilde{h} = 2^{c-1} r\left[-\frac{1}{8},\frac{1}{8},1,1,\frac{1}{8},-\frac{1}{8}\right] \qquad \tilde{g} = 2^{c-1}[1,-1]$$

where c and $r = (1 + 2^{-5})^{-1/2}$ are normalizing facto $(\tilde{h},\tilde{g})$ are the analysis and synthesis filter banks With this, the Bi-Haar coefficients will have the sa as the Haar ones at each scale. The establish orthogonal Haar wavelet transform is done b procedure suggested by Zhang *et al.* (2008). T PURE transformation with bi-Haar is applied image producing multiple transformed versions o noisy image. These two-dimensional data se converted to one-dimensional signals such that scales are identically ordered between the respe The statistical redundancy between the data strea by first calculating and then applying the IC matrix to the data. These independent data stre individually denoised using a given denoising te process is then inverted to recover the now den first by applying the ICA mixing matrix a respective inverse DWT's. These are then averag produce the final denoised version of the origina The proposed denoising model allows for the

additional wavelet decompositions of the original image. The outcome is the ability to utilize greater combinations of wavelets to effectively capture a wider range of image characteristics. In particular, this approach enables the application of different wavelets along rows and columns respectively while incorporating all of the possible orientations from the selected wavelets.

V. Experimental Results

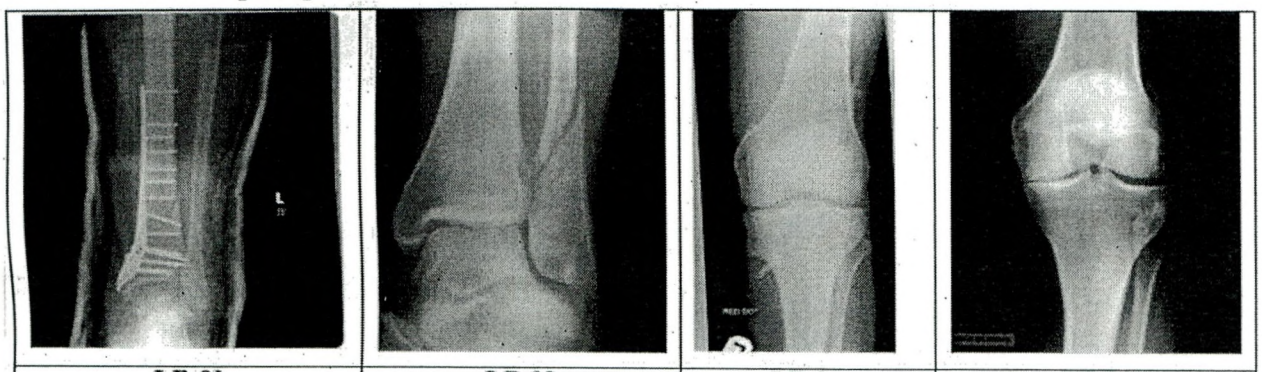
Several experiments were conducted to evaluate the proposed despeckling model. The performance metrics used are (i) Peak Signal to Noise Ratio (PSNR) and (ii) Denoising Time. PSNR is a quality measurement between the original and a denoised image. The higher the PSNR, the better the quality of the compressed or reconstructed image.

To compute PSNR, the block first calculates the Mean-Squared Error (MSE) and then the PSNR (Equation 15).

$$PSNR = 10 \log_{10}\left[\frac{R^2}{MSE}\right] \quad \text{where } MSE = \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N} \qquad (15)$$

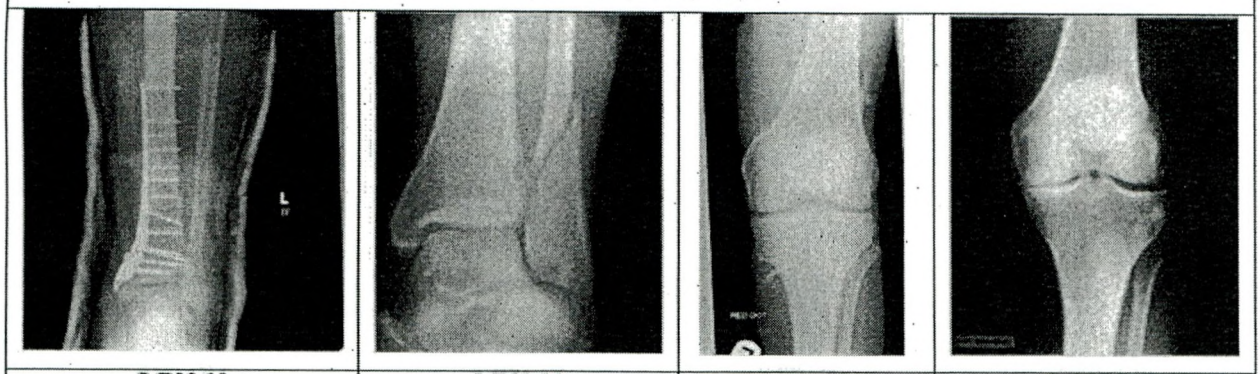
where M and N, m and n are number of rows and columns in the input and output image respectively

Denoising time denotes the time taken for the algorithm to perform the despeckling procedure. Further, the proposed method was compared with Conventional Wavelet Model, ICA denoising Model and Base Model. Several images were used to test the proposed model. The results projected in this chapter uses the four test images shown in Figure 4. Figure 5 shows the images after Poisson noise is added. The proposed models were implemented using MATLAB 7.3 and were tested on Pentium IV machine with 512 MB RAM.



LB-01 | LB-02 | LB-03 | LB-04

Figure 4 : Test Images



LBN-01 | LBN-02 | LBN-03 | LBN-04

Figure 5 : Noisy Images

The quality of denoised image against the noisy image is determined by using the PSNR value. The PSNR values obtained for the different filters are tabulated in Table 1.

From the projected figures, it is evident that the proposed method is efficient in image quality when compared to all the models. The high PSNR obtained by the proposed model indicates that it is the best choice for removing Poisson noise from ultrasound images. The average PSNR obtained for each technique is shown in Figure 6.

According to Venkatesan *et al.* (2008), an improved denoising algorithm is recognized by a high PSNR or a lower MSE. In agreement with this, the results of the proposed systems show high PSNR, which proves that they are an improved version over existing methods. Similarly, according to the report of Schneier and Abdel-Mottaleb (1996), a PSNR value in the range 30-40 indicates that the resultant image is a very good match to the original image. In accordance with this report, the results of all the three the proposed hybrid algorithms produce PSNR values in the range 40-46dB proving that it is an enhanced version when compared with the conventional algorithms.

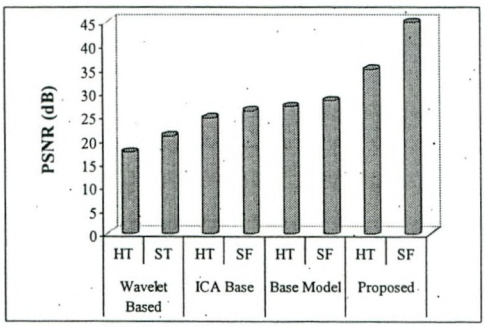


Figure 6 : Average PSNR

TABLE 1
PSNR PERFORMANCE

Images	Wavelet Based		ICA Base		Base Model		Proposed	
	HT	ST	HT	SF	HT	SF	HT	SF
LBN-01	25.15	26.77	20.17	21.84	26.70	28.41.	33.21	46.62
LBN-02	23.68	25.61	16.17	20.39	22.14	26.22	34.23	42.91
LBN-03	24.46	25.74	18.75	21.78	28.80	30.03	36.24	52.90
LBN-04	25.33	29.34	14.27	19.08	22.58	26.51	38.90	40.96

The average time taken to denoise an image is shown in Figure 7.

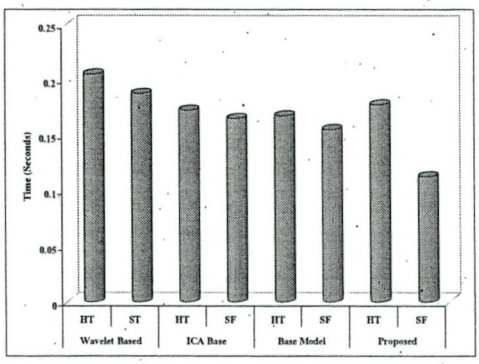


Figure 7 : Average Denoising Time

The figure shows that the proposed model while using soft threshold is quick in removing Poisson noise, but its speed performance degrades while using hard threshold. However, the performance of hard thresholding in terms of both PSNR and time, is poor when compared to soft threshold. It can be concluded that the proposed system outperforms all the others models in terms of time.

According to Müldner *et al.* (2005), PSNR and speed are the two most important performance factors of any denoising algorithm. From the results, it is evident that the speed of the proposed denoising algorithms are faster when compared to the standard algorithms and therefore makes it an attractive option for several advanced applications in the field of medical imaging.

The visual comparison of the denoised image produced by the various conventional and proposed filters while using soft thresholding for image LBN-1 is shown in Figure 8

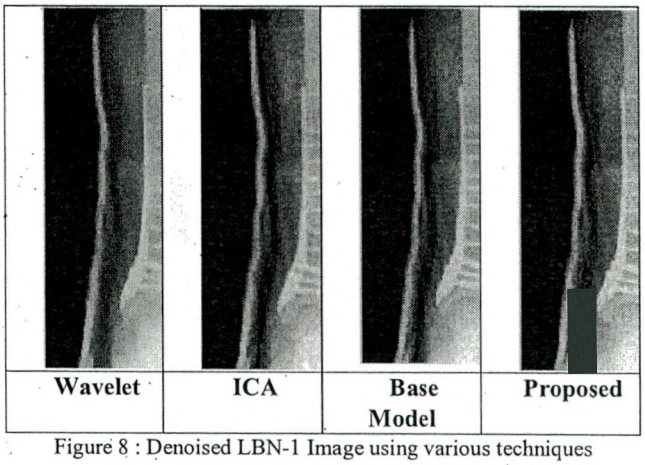


Figure 8 : Denoised LBN-1 Image using various techniques

VI. CONCLUSION

Denosing X-Ray images is a vital step in correct diagnosis of fractures. X-Ray images are generally contains Poisson noise, which degrades the image and makes the diagnosis a difficult process. The healthcare practitioners require method which while removing noise from X-Ray images preserves important diagnostic data. This study proposed a method that combined bi-orthogonal Harr wavelet combined with ICA to remove Poisson noise from X-Ray images. The thresholding method used was BayesShrink operator and both soft and hard thresholding were analyzed. From the experimental results, it is evident that the proposed model produces images which are visually clean and smooth in fast manner. At the same time, the proposed method also preserves edges and other significant details of the image. As the method presented in this paper is part of fracture detection system, in future, the affect of the same on fracture detection is planned to be analyzed.

REFERENCES

[1] Delakis, I., Hammad, O. and Kitney, R.I.(2007) Wavelet-based de-noising algorithm for images acquired with parallel magnetic resonance imaging (MRI), Physics in Medicine and Biology, Vol. 52, No.13, Pp.3741.

[2] Donoho, D.L. and Johnstone, I.M. (1995) Adapting to unknown smoothness via wavelet shrinkage. Journal of the American Statistical Association, Vol. 90, No. 432, Pp. 1200-1224.

[3] Federico, A. and Kaufmann, G.H. (2007) Denoising in digital speckle pattern interferometry using wave atoms, Opt. Lett., Vol. 32, Pp.1232-1234.

[4] Hoyer, P. (1999) Independent Component Analysis in Image Denoising, Master's Thesis, Helsinki University of Technology.

[5] Hyvarinen, A. (1999) Sparse code shrinkage : Denosing of Non-Gaussian data by maximum likelihood estimation, Neural Computation, Vol. 11, No. 7, Pp. 1739-1768.

[6] Hyvarinen, A., Oja, E. and Hoyer, P. (2000) Image denoising by Sparse Code shrinkage, S. Haykin and B. Kosko (Eds.), Intelligent Signal Processing, IEEE Press.

[7] Ibrahim, F., Osma, N.A.A., Usma, J. and Kadri, N.A. (2007) Feature extraction in Medical Ultrasonic Image, 3rd Kuala Lumpur International Conference on Biomedical Engineering, IFMBE Proceedings, Springer Brlin Heidelberg, Vol.15, Pp.267-270.

[8] Kaur, A. and Singh, K. (2010) Speckle noise reduction by using wavelets, National Conference on Computational Instrumentation CSIO NCCI 2010, INDIA, Pp. 198-203.

[9] Luisier, F., Vonesch, C., Blu, T. and Unser, M. (2010) Fast interscale wavelet denoising of Poisson-corrupted images, signal Processing, Elsevier, Pp. 415–427.

[10] Marusic, S., Deng, G., Tay, D.B.H. (2005) Image Denoising Using Over-complete Wavelet Representations, Proceedings of the European Signal Processing Conference, EUSIPCO 2005, Pp. 1-4.

[11] Müldner, T., Leighton, G. and Diamond, J. (2005) Using XML compression for WWW communication, Proceedings of the IADIS WWW/Internet 2005 Conference.

[12] Niijima, M. (2000) Wavelet image analysis. Kagaku Gijutsu Publishing (in Japanese).

[13] Sakata, M. and Ogawa, K. (2009) Noise reduction and contrast enhancement for small-dose X-Ray images in wavelet domain, IEEE Nuclear Science Symposium Conference Record (NSS/MIC), Orlando, FL, Pp. 2924-3654.

[14] Schneier, M. and Abdel-Mottaleb, M. (1996) Exploiting the JPEG compression scheme for image retrieval, IEEE Trans. Pattern Anal. Mach. Intell., Vol.18, No. 8, Pp. 849–853.

[15] Sudha, S., Suresh, G.R. and Sukanesh, R. (2009) Comparative Study on Speckle Noise Suppression Techniques for Ultrasound Images, International Journal of Engineering and Technology Vol. 1, No. 1, Pp. 1793-8236.

[16] Tsukahara, M., Haseyama, M. and Kitajima, H. (1998) Removal of additive white noise using an adaptive Wiener filter with edge retention, Trans IEICE 1998, J81-DII: 623–631.

[17] Venkatesan, M., MeenakshiDevi, P., Duraiswamy, K. and Thyagarajah, K. (2008) Secure Authentication Watermarking for Binary Images using Pattern Matching, IJCSNS International Journal of Computer Science and Network Security, Vol.8, No.2, Pp. 241-250.

[18] Wang, L., Lu, J., Li, Y., Yahagi, T. And Okamoto, T. (2008) Noise Removal for Medical X-Ray Images in Wavelet Domain, Electrical Engineering in Japan, Vol. 163, No. 3, Translated from Denki Gakkai Ronbunshi, Vol. 126-C, No. 2, Pp. 237–244.

[19] Zhang, B., Fadili, M.J., Starck, J.L. and Digel, S.W. (2008) Fast Poisson noise removal by biorthogonal Haar domain hypothesis testing, Statistical Methodology, Journal of the International Indian Statistical Assocaition, Elsevier, Vol. 5, Pp. 387–396.

[20] Zhang, Q., Yin, H. and Allinson, N.M. (2000) A simplified ICA based denoising method, Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks, IJCNN 2000, Como, Italy, Vol. 5, Pp. 479-482.

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