IMPROVED HYBRID MODEL FOR DENOISING POISSON CORRUPTED X-RAY IMAGES

N. Umadevi

HOD of computer Science
Sri Jayendra Saraswathi College of Arts & Science
Coimbatore - 641005
Email : umadevigayathri@rediffmail.com

Dr. S.N.Geethalakshmi

Associate Professor
Avinashilingam Deemed University
Coimbatore - 641043
Email : sngeethalakshmi@yahoo.com

ABSTRACT

Medical practitioners are increasingly using digital images during disease diagnosis. Several state-of-the-art medical equipments are producing images of different organs, which are used during various stages of analysis. Examples of such devices include MRI, CT, ultrasound and X-Ray. Out of these, X-Ray is one the oldest and frequently used devices, as they are non-intrusive, painless and economical. The X-Ray images are normally affected by Poisson noise. The noise in the image has two disadvantages, the first being the degradation of the image quality and the second, more important, obscures important information required for accurate diagnosis. The main aim of any denoising algorithm is to remove noise while preserving important diagnostic data. This study combines two works that uses wavelets and Independent Component Analysis (ICA) to form a hybrid model that uses ICA technique coupled with Multiple Wavelet Denoising (MWD) Structure to remove noise. All the three works aim to remove Poisson noise from X-Ray images. Several experiments were conducted. The performance of the proposed system is analyzed in terms of Peak Signal to Noise Ratio and speed of denoising and a comparison is presented with the existing system.

Keywords : Poisson Noise, X-Ray Image Denoising, Wavelet Denoising, ICA Denoising, PureShirnk, Hybrid Denoising.

1. INTRODUCTION

Medical image processing is a field of science that is gaining wide acceptance in medical industry due to its technological advances and software breakthroughs. Medical image processing is the use of the algorithms and procedures for operations such as image enhancement, image compression, image analysis, mapping, geo-referencing, etc. 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. It plays a vital role in disease diagnosis and helps the medical practitioners during decision making with regard to the type of treatment. The influence and impact of digital images on healthcare industry is tremendous and contributes a great deal in improved patient care.

Several state-of-the-art equipments that produce human organs in digital form used during treatment include 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. The visual distortion might arise due to various factors like, time of exposure, lighting, movement of patient, sensitivity of the imaging devices, etc., and affect images in terms of contrast, distortion and artifacts introduced, blur and contrast sensitivity. These visual changes have negative impact and make the image complex for interpretation. This necessitates image enhancement techniques that improve these quality parameters. Examples include histogram equivalization, image smoothening, image sharpening, contrast adjustment, edge or boundary enhancement and denoising (Thangam *et al*., 2009).

Out of these, image denoising has become very essential in medical image analysis. Almost all medical images, which are acquired using different devices, are affected by a distortion metric, called 'Noise'. Each device introduces different kind of noise. For example, ultrasound images are mostly degraded by 'Speckle Noise', while X-Ray images are often have 'Poisson noise'. Noise in images, in particular, medical images, have two disadvantages. They are (i) degradation of the image quality and (2) obscuring important information required for accurate diagnosis. As both these points have serious impact, they have to be handled in an efficient manner.

Thus, all medical imaging devices need some denoising algorithm to enhance the image under consideration and thus help the medical practitioner to make diagnosis quickly and efficiently.

The main objective of any X-ray image denoising technique is to remove noises introduced during acquisition and transmission, while retaining as much as possible the important signal features (Sudha et al., 2009). This process is considered as a challenging research area because they are irreversible and often non-noisy regions are removed as noisy regions. For example, a tumour presence should not be considered as noise.

Several researchers have concentrated on producing solutions to remove noise from X-Ray images but the field is still immature and a 100% solution is not yet achieved. In this paper, three such solutions, all with a common aim of removing Poisson noise in X-Ray images, are studied and compared. They are (i) wavelet denoising for Poisson noise removal (ii) Independent Component Analysis (ICA) for Poisson noise removal and (iii) a hybrid model that combines wavelets and ICA for Poisson noise removal. The rest of the paper is organized as below. Section 2 presents an overview to X-Ray images and presents some previous works related to denoising X-Ray images. Section 3 presents the wavelet denoising model while Section 4 discusses the ICA denoising model. The proposed hybrid model is discussed in Section 5. The results of comparison are presented in Section 6 and the paper is concluded with future research directions in Section 7.

2. X-RAY IMAGES AND EXISTING DENOSING METHODS

In this paper, the noise in X-Ray images is considered. An X-Ray (radiograph) is a non-invasive 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 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 'PURESHRINK' in this paper. PURESHRINK uses Haar wavelet transformation with soft thresholding to reduce Poisson noise in an image. This method has the advantage that while performing efficient Poisson denoising in a time efficient manner, in some cases, it introduced 'staircase' artifacts. In this paper, the PURESHRINK 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. All the techniques used soft thresholding. 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.

2. 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 1.

$$I(t) = O(t) + N(t) \tag{1}$$

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).

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, 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, 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.

(i) Threshold operators

Most frequently used thresholding methods are soft and hard thresholding. The hard and soft thresholding operations are defined as in Equations (2) and (3).

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

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

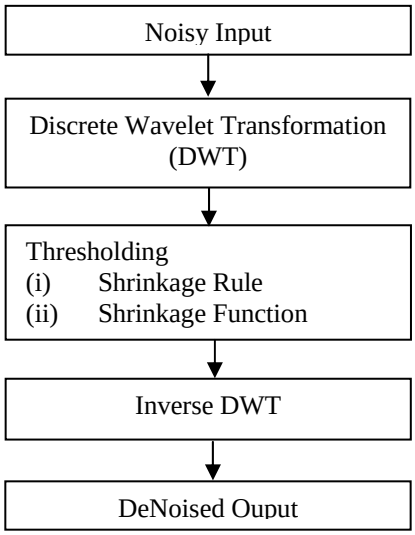


Figure 1 : Wavelet Denoising

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 2a,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.

(ii) Selection of threshold

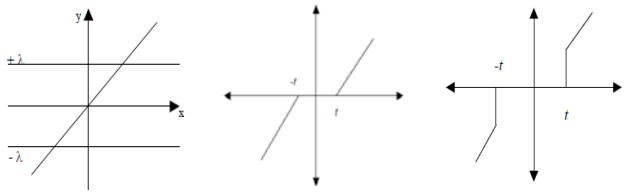
The selection of threshold is the most important step in any wavelet based denoising model. Careful selection is needed because a small threshold will produce an image which is still noisy, while a large threshold destroys details and produces blurs and artifacts. Two types of thresholding techniques, 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 4.

$$\lambda = \sigma\sqrt{2\log(M)} \qquad 4$$

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 5)

$$\sigma = \frac{\sum_{i=0}^{N-1} (X_j)^2}{N} \qquad (5)$$

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



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

Figure 2 : Effect of Thresholding

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

$$t_B = \sigma^2/\sigma_s^2 \tag{6}$$

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,

$$w(x, y) = s(x, y) + n(x, y) \tag{7}$$

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

$$\sigma^2_w = \sigma^2_s + \sigma^2_w \tag{8}$$

$\sigma^2 w$ can be computed using Equation (9). From this the variance of the signal, σ^2_s can be computed using Equation (10).

$$\sigma_w^2 = \frac{1}{n^2} \sum_{x,y=1}^{n} w^2(x, y) \tag{9}$$

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2, 0)} \tag{10}$$

with σ^2 and σ^2_s, the Bayes threshold is computed from Equation (6). In this paper, the Bayes threshold method is used.

3. 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.

4. HYBRID 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 an 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

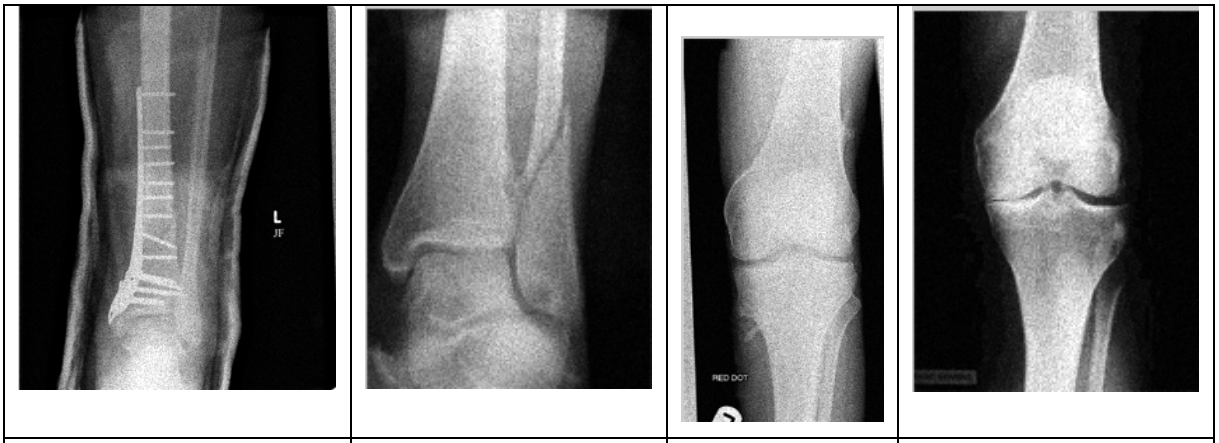
$$\theta_n^{\text{PUREshrink}}(d,s;a) = \text{sign}(d_n)\max(|d_n| - a\sqrt{|S_n|},0) \qquad (11)$$

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 weights are unknown. It is these weights that are then computed by minimizing the PURE, through the resolution of a simple linear system of equations. This means that all the parameters of the algorithm are adjusted completely automatically, without requiring user input. The advantage obtained is that, the thresholds are adapted to local estimates of the (signal-dependent) noise variance. These estimates are derived from the corresponding low-pass coefficients at the same scale; the latter are also used to incorporate interscale relationships into the denoising functions. The resulting procedure can be easily integrated into the wavelet decomposition, which is non-redundant. The MSE estimate is optimized independently for each subband by exploiting the orthogonality of the Haar wavelet basis. As a result, the algorithm has low computational complexity and modest memory requirements. These are valuable features for denoising large datasets, such as those typically produced in medical applications. Importantly, this computational efficiency is not traded for quality. On the contrary, the algorithm yields improved results.

The Haar wavelet used in this paper, the orthogonal Haar wavelet framework of PURE is combined with a biorthogonal Haar wavelet transform. Haar wavelet provides a manageable distribution over wavelet coefficients. But due to the lack of continuity of Haar filters, its estimate can be highly irregular with strong "staircase" artifacts when decimation is involved. To solve this dilemma between distribution manageability and reconstruction regularity, the use of Bi-Haar wavelet is proposed. Its implementation filter bank is given by:

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

Figure 3 : Test Images



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

Figure 4 : Noisy Images

$$h = 2^{-c}[1,1] \qquad g = 2^{-c} r\left[\frac{1}{8},\frac{1}{8},-1,1,-\frac{1}{8},-\frac{1}{8}\right] \qquad (12)$$

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

where c and r = $(1 + 2^{-5})^{-1/2}$ are normalizing factors, (h, g) and $(\tilde{h}, \tilde{g})$ are the analysis and synthesis filter banks respectively. With this, the Bi-Haar coefficients will have the same variance as the Haar ones at each scale. The establishment of bi-orthogonal Haar wavelet transform is done by using the procedure suggested by Zhang *et al*. (2008). The modified PURE transformation with bi-Haar is applied to the input image producing multiple transformed versions of the original noisy image. These two-dimensional data sets are then converted to one-dimensional signals such that the relative scales are identically ordered between the respective signals. The statistical redundancy between the data streams is reduced by first calculating and then applying the ICA unmixing matrix to the data. These independent data streams are then individually denoised using a given denoising technique. The process is then inverted to recover the now denoised images, first by applying the ICA mixing matrix and then the respective inverse DWT's. These are then averaged together to produce the final denoised version of the original noisy image. The proposed denoising model allows for the inclusion of 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.

4. EXPERIMENTAL RESULTS

Several experiments were conducted to evaluate the proposed 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 13).

Table II : DENOISING TIME (Seconds)

Image	Wavelets	ICA	PureShrink	Hybrid
LBN-01	0.19	0.16	0.16	0.11
LBN-02	0.19	0.18	0.15	0.11
LBN-03	0.18	0.16	0.16	0.12
LBN-04	0.19	0.16	0.15	0.11

$$\text{PSNR} = 10 \log_{10}\left[\frac{R^2}{MSE}\right] \text{ where MSE} = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N} \text{ where M and N, m and n are} \qquad (13)$$

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 3. Figure 4 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.

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 shown in Table I. Average PSNR of the four images was calculated to ascertain the overall performance of the systems in terms of PSNR and is shown in Figure 5.

From the projected figures, it is evident that the proposed hybrid method is an improved version of the existing systems. The high PSNR obtained by the proposed model indicates that it is the better choice for removing Poisson noise from ultrasound images.

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 (40-49 dB), 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 the proposed hybrid algorithm produce average PSNR value of 44.84 dB and therefore can be considered as an enhanced version.

Speed of denoising is another factor that is very important in medical image processing. The performance of time taken by the algorithms is tabulated in Table II and the average time taken to denoise is shown in Figure 6.

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.

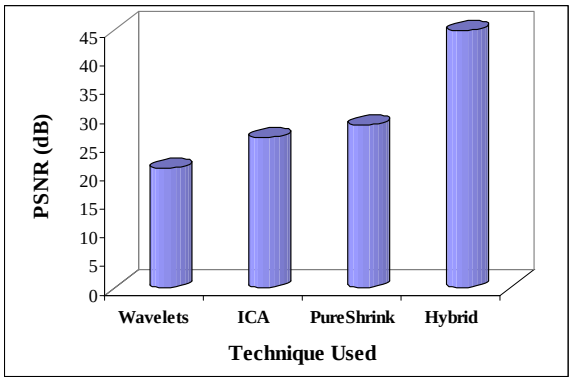


Figure 5 : PSNR Performance

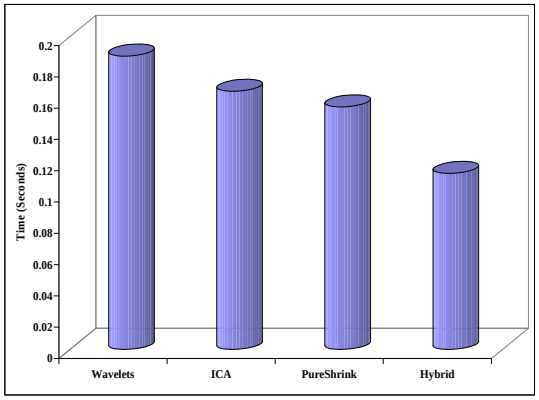


Figure 6 : Average Denoising Time

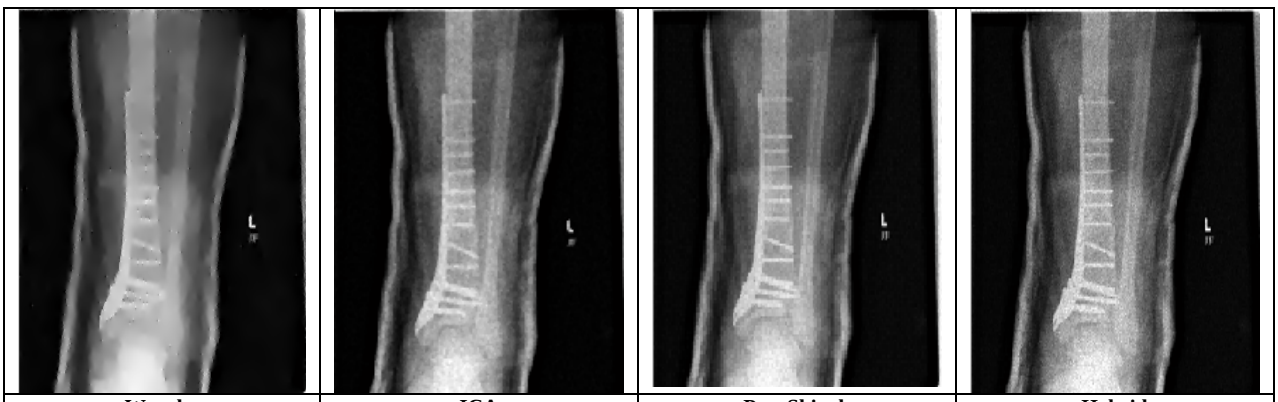
Table I : PSNR

Image	Wavelets	ICA	PureShrink	Hybrid
LBN-01	21.84	26.77	28.41	46.62
LBN-02	20.39	25.61	26.22	42.91
LBN-03	21.78	25.74	30.03	48.90
LBN-04	19.08	26.34	28.51	40.96

The visual comparison of the denoised image produced by the existing and proposed denoising techniques for image LBN-1 is shown in Figure 7. Similar results were visualized for other images also.

5. CONCLUSION

This paper analyzed denosing of X-Ray images using wavelets, ICA and PURESHRINK and proposed a method that enhanced the PURESHRINK technique to reduce Poisson noise. Several experiments were conducted to analyze the performance of the proposed system and the results proved that the the hybrid combination of bi-orthogonal Haar wavelets with BayesShrink thresholding method and ICA is an enhanced version of the existing models. The proposed method was able to achieve good quality images in a relative fast manner and preserved significant details of the image. In future, the edge preserving capacity of the algorithm is to be ascertained and its effect on segmentation of X-ray images is to be studied.



Wavelet	ICA	PureShirnk	Hybrid

Figure 7 : Visual Comparison

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Author Biography

Dr.S.N.Geethalakshmi working as Reader in the Department of Computer Science, Avinashilingam University for Women. She has nineteen years of teaching experience and ten years of research experience. Her area of interest is Image Processing, Software engineering. Her publications include 3 International journals, 3 National Journals, 9 International Conferences, 3 National Conferences and 2 National Articles.

N.Umadevi working as Head in the Department of Computer Science and Information Technology, Sri Jayendra Saraswathy Maha Vidyalaya College of Arts and Science, Singanallur,Coimbatore is a research scholar of Avinashilingam University for women. She has 3 years of industrial experience and 9 years of teaching experience. Her area of interest are Image Processing and Data Mining. Her publications include 2 International Journals. She has presented papers in 2 International Conferences and 4 National Conferences.