Image Denoising And Enhancement Using Multiwavelet With Hard Threshold In Digital Mammographic Images

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Abstract: *Breast cancer continues to be a significant public health problem in the world. The diagnosing mammography method is the most effective technology for early detection of the breast cancer. However, in some cases, it is difficult for radiologists to detect the typical diagnostic signs, such as masses and microcalcifications on the mammograms. Dense region in digital mammographic images are usually noisy and have low contrast. And their visual screening is difficult to view for physicians. This paper describes a new multiwavelet method for noise suppression and enhancement in digital mammographic images. Initially the image is pre-processed to improve its local contrast and discriminations of subtle details. Image suppression and edge enhancement are performed based on the multiwavelet transform. At each resolution, coefficient associated with the noise is modelled and generalized by laplacian random variables. Multiwavelet can satisfy both symmetry and asymmetry which are very important characteristics in Digital image processing. The better denoising result depends on the degree of the noise, generally its energy distributed over low frequency band while both its noise and details are distributed over high frequency band and also applied hard threshold in different scale of frequency sub-bands to limit the image. This paper is proposed to indicate the suitability of different wavelets and multiwavelet on the neighbourhood in the performance of image denoising algorithms in terms of PSNR.. Finally it compares the wavelet and multiwavelet techniques to produce the best denoised mammographic image using efficient multiwavelet algorithm with hard threshold based on the performance of image denoising algorithm in terms of PSNR values.*

Keywords: *Mammographic , Image denoising, Wavelet, Multiwavelet , PSNR, Enhancement*

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1. Introduction

Breast cancer currently accounts for more than 38% of cancer incidence and a significant percentage of cancer mortality in both developing and developed countries. It has been shown that early detection and treatment of breast cancer are the most effective methods of reducing mortality.

Despite of advances in resolution and film contrast, screen film mammography remains a diagnostic imaging modality where image interpretation is very difficult. Breast radiographs are generally examined for the presence of malignant masses and indirect signs of malignancy such as micro calcifications and skin thickening. A significant effort has been directed to improve imaging performance, but it is unlikely that improvements will be achieved only by advances in screen film radiography.

In general, the visualization of mammograms displays a small percentage of the information available. This deficiency of the mammographic technology is caused by the fact that, in general, there are small differences in X-ray attenuation between normal glandular and malignant tissues[9]. Detection of small malignancies is specially difficult in younger women who tend to present denser breast tissue. On the other hand, calcifications have high attenuation properties (because these are denser tissues, similar to bones), but are small in size, and tend to present low local contrast Therefore, the visibility of small tumors and any associated micro calcifications, is a problem in the mammography technology based on analog film. Mammographic images are inherently noisy and usually contain low contrast regions. In fact it is a challenge to improve the visual quality of mammograms by image processing for helping in the early detection of breast cancer. Therefore, two important current problems in mammographic image processing are: (a) improvement of local detail discrimination in low contrast regions and (b) noise reduction in such images without blurring fine image details.This paper proposes a method for enhancing dense mammograms that can be useful for the detection of clustered microcalcifications[14]. Their method was tested on scanned images, and for each image, precise equipment calibration and parameter adjustments are required (and also an initial selection of the region of interest). However, nowadays, there is a severe time constant in medical services provided to the public, where many mammograms must be screened daily. In this work we are interested in less time consuming enhancement methods that minimize the need for parameter adjustments by the user.

Local contrast and image intensity are inter-dependent in mammographic images. In fact, noise tends to increase with pixel intensity in such images making the discrimination of local details more difficult, specially in dense regions.

The noise equalization procedure has been proposed as a preprocessing stage to automatic micro calcification detection, which can downgrade some image structures for visual screening. However, automatic microcalsification detection algorithms often produce false positives (and false negatives), making direct visual screening necessary to obtain reliable diagnoses. As a consequence, techniques for improving direct visual screening of mammograms are needed in clinical practice.

The main problem of the earlier approaches that a noise estimate is needed, which may be difficult to obtain in practical situations[9], specially for images with inherent noise (e.g. X-ray images, aerial images, etc.) In fact, the reported probabilistic approaches were not sufficiently tested for these types of images.

Previously, Discrete Wavelet Transform (DWT) multiply ever scale by a weight factor and then reconstruct an image using the inverse DWT. The weights are determined by supervised learning, given as set of training cases. However, the DWT is not translation invariant, meaning that a shift in the image origin leads to results inherently different to the transform applied to the original image.

This method cannot be applied for mammographic image enhancement in general, because the size and the shape of the suspicious structures vary significantly in mammograms.

The New adaptive method for mammographic image denoising and enhancement using the wavelet transform, which combines noise equalization, wavelet shrinkage and scale-space constraints. Existing wavelet shrinkage function given the poor quality with low PSNR values. Our multiwavelet approach is flexible enough to allow the user to select the desired image enhancement and scale of analysis, but it does not require the user to adjust any parameters for image denoising.

The problem of Image de-noising can be summarized as follows. Let A(i,j) be the noise-free image and B(i,j)the image corrupted image with independent Gaussian noise Z(i,j),

$$B(i,j)= A(i,j)+\sigma Z(i,j) \qquad (1)$$

where Z(i,j) has normal distribution N(0,1) . The problem is to estimate the desired signal as accurately as possible according to some criteria. In the wavelet domain, if an orthogonal wavelet transform is used, the problem can be formulated as

$$Y(i,j)= W(i,j)+N(i,j) \qquad (2)$$

where Y(i,j) is noisy wavelet coefficient; W(i,j) is true coefficient and N(i,j) noise, which is independent Gaussian

In multi-wavelet aspects, the symmetry and dissymmetry of the wavelet is rather important in signal processing. But single-wavelets with orthogonal intersection and compact-supporting are not symmetric except Harr. Recently, research on multi-wavelet is an active orientation. As multi-wavelet can satisfy both symmetry and asymmetry these are very important characters in signal processing. Multi-wavelet is commonly used in image compression, image de-noising, digital watermark and other signal processing field, so it is especially appropriate to processing complex images.

There are r compact-supporting scaling functions $\phi=(\phi_1,\phi_2,\ldots\phi_r)^T$ and they are inter-orthogonal with the wavelet functions $\psi=(\psi_1,\psi_2,\ldots\psi_r)^T$ $\phi_r(t)(l=1,2,\ldots r)$. The orthogonal basis of $L^2(R)$ space is $2^{j/2}\psi_r(2^j t-k)(j, k\in Z,\ l=1,2,\ldots,r)$. H_k, G_k are the $N*N$ matrix finite response filters with orthogonal basis, then the following specific equations can be obtained:

$$\phi(t)=\sum_{k\in z} H_k\phi(2t-k)$$
$$\psi(t)=\sum_{k\in z} H_k\phi(2t-k)$$

2. The Pre-Processing State

2.1. Contrast Enhancement

All radiological images contain random fluctuations due to the statistics of X-ray quantum absorption. This noise makes the detection of small and subtle structures more difficult. Usually, the relationship between image intensity and noise variance is nonlinear, and varies significantly from image to image.

In this paper, preprocessing method is extended for use on direct screening of digital mammograms. Within a neighborhood Q of an image location (x,y) the local contrast is estimated as :

$$c(x,y) = f(x,y) - \text{median}_Q(x,y) \qquad (3)$$

where $c(x,y)$ is the estimated local contrast, $f(x,y)$ is the image gray level at (x,y), and median $_Q(x,y)$ is the median gray level within the neighbours $_Q$ of (x,y) Eq. (3) takes the form of a high-pass spatial filter, a local contrast provides a measure of the high frequency image noise. The noise associated with each image gray level I can be measured by the local contrast standard deviation $\sigma_c(I) \equiv \sigma\{c(I)\}$ (i.e by the local contrast variability considering all pixels with gray level I).

3. The Wavelet Transform

To compute the redundant wavelet transform with two detailed images, a smoothing function $\phi(x,y)$ and two wavelets $\psi^j(x,y)$ are needed. The dilation of these functions are denoted by

$$\phi_s(x,y) = \frac{1}{s^2}\,\phi_s\left(\frac{x}{s},\frac{y}{s}\right),$$

$$\psi^j_s(x,y) = \frac{1}{s^2}\,\psi,$$

$$\left(\frac{x}{s},\frac{y}{s}\right), = I = 1, 2 \qquad (4)$$

and the dyadic wavelet transform $f(x,y)$ at a scale s = 2^j, has two detail components, given by

$$W^1_{2j} f(x,y) = (f * \Psi^1_{2j})(x,y),\ i = 1,2 \qquad (5)$$

and one low-pass component, given by

$$S_{2j} f(x,y) = (f * \phi_{2j})(x,y) \qquad (6)$$

There coefficients $W^1_{2j} f(x,y)$ and $W^2_{2j} f(x,y)$ represent the details in the *x* and *y* directors, respectively. Thus, the image gradient at the resolution 2^j can be approximated by

$$W_{2j} f(x,y) = \begin{pmatrix} W^1_{2j} f(x,y) \\ W^2_{2j} f(x,y) \end{pmatrix} \qquad (7)$$

The Multi-Wavelet Transform of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared to other multi-scale representations such as Gaussian and Laplacian pyramid. Recently, Multi-Wavelet Transform is preferred for image de-noising.

Multi-wavelet iterates on the low-frequency components generated by the first decomposition. After scalar wavelet decomposition, the low-frequency components have only one sub-band, but after multi-wavelet decomposition, the low-frequency components have four small sub-bands, one low-pass sub band and three band-pass sub bands. The next iteration continued to decompose the low frequency components $L=\{L_1L_1,\ L_1L_2,\ L_2L_1,\ L_2L_2\}$. In this situation, a structure of $5(4*J+1)$ sub-bands can be generated after *J* times decomposition, as shown in figure 1. The hierarchical relationship between every sub-band is shown in figure 2. Similar to single-wavelet, multi-wavelet can be decomposed to 3 to 5 layers.

The Gaussian noise will near be averaged out in low frequency Wavelet coefficients. Therefore only the Multi-Wavelet coefficients in the high frequency level need to hard be threshold.

L_1L_1	L_1L_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2H_1	L_2H_2
H_1L_1	H_1L_2	H_1H_1	H_1H_2
H_2L_1	H_2L_2	H_2H_1	H_2H_2

Figure 1. The structure of sub-band distribution.

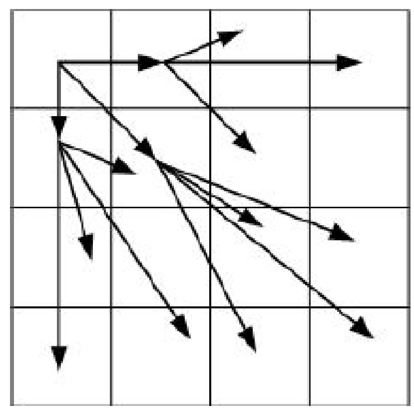


Figure 2. The hierarchical relationship between every sub-band.

4. Threshold for Wavelet

The following are the methods of threshold selection for image denoising band in Wavelet transform.

4.1. Method 1: Visushrink

Threshold T can be calculated using the formulae,
$T= \sigma\sqrt{2\log n^2}$

\This method performs well under a number of applications because wavelet transform has the compaction property of having only a small number of large coefficients. All the remaining wavelet coefficients are very small. This algorithm offers the advantages of smoothness and adaptation. However, it exhibits visual artifacts.

4.2. Method 2: Neighshrink

Let d(i,j) denote the wavelet coefficients of interest and B(i,j) is a neighborhood window around d(i,j). Also let $S^2=\sum d^2(i,j)$ over the window B(i,j). Then the wavelet coefficient to be thresholded shrinks according to the formulae,

$$d(i,j)= d(i,j)* B(i,j) \qquad (8)$$

where the shrinkage factor can be defined as $B(i,j) = (1- T^2/ S^2(i,j))_+$, and the sign + at the end of the formulae means to keep the positive value while set it to zero when it is negative.

4.3. Method3: Modineighshrink

During experimentation, it was observed that when the noise content was high, the reconstructed image using Neighshrink contained mat like aberrations. These aberrations could be removed by wiener filtering the reconstructed image at the last stage of IDWT. The cost of additional filtering was slight reduction in sharpness of the reconstructed image. However, there was a slight improvement in the PSNR of the reconstructed image using wiener filtering. The de-noised image using Neighshrink sometimes unacceptably gets blurred and lost some details. The reason could be the suppression of too many detail wavelet coefficients. This problem will be avoided by reducing the value of threshold itself. So, the shrinkage factor is given by

$$B(i,j) = (1 - (3/4)*T^2 / S^2(i,j))_+ \quad (9)$$

5. Hard Threshold For Multi-Wavelet

The key of wavelet threshold in image de-noising is how to evaluate the coefficients. Although the methods of hard and soft threshold are widely in practice, there are many faults in their nature. When hard threshold is to keep datum greater than the threshold, and all data less than the threshold are put to zero, the formula is as following:

$$A'_{j,k} = \begin{cases} A_{j,k} \cdots\cdots |A_{j,k}| \geq \sigma \\ 0 \cdots\cdots\cdots |A_{j,k}| < \sigma \end{cases} \quad (10)$$

Where σ is threshold and $A_{j,k}$ the wavelet coefficients. When hard threshold, $A_{j,k}$ are discontinuous at σ will bring some concussions and large mean-square deviation to the reconstructed signal.

6. De-Noising Process for Multi-Wavelet:

If the noised image

$$I(i,j) = X(i,j) + n(i,j) \quad i,j=1,2,\ldots,N \quad (11)$$

Where $n(i, j)$ is white Gaussian noise whose mean value is zero, σ is its variance, and $X(i,j)$ the original signal. The problem of de-noising is how to recover $X(i, j)$ from $I(i, j)$. Formula (12) is obtained when formula (11) is applied with multiwavelet

$$W_I(i,j) = Wx(i,j) + W_n(i,j) \quad (12)$$

It is known from multi-wavelet transformation that the multi-wavelet transformation of Gaussian noise is also Gaussian distributed[1]. There are components at different scales, but energy distributes evenly in high frequency area, and the specific signal of the image has projecting section in every high frequency components. So image de-noising can be performed in high frequency area of multi-wavelet transformation. Reconstructed image can be obtained by using the inverse multi-wavelet transform. The realizing process is as follows for multi-wavelet:

- Decompose the noised image by multi-wavelet transformation, the decomposing level is *J*.
- Make statistic to the energy distribution of every small sub-bands.
- The initial threshold can be selected according to $\lambda=\sigma\sqrt{2\log n2}$.
- Fix thresholds of every sub-band
- Calculate wavelet coefficients of every level
- Perform inverse multi-wavelet transform by using the high and low frequency coefficients obtained by process upwards, and get the de-noised image $Xr(i, j)$ according to multi-wavelet recreation formula of two-dimension image.

7. Evaluation Criteria For Wavelet And Multi-Wavelet

The above said methods are evaluated using the quality measure Peak Signal to Noise ratio which is calculated using the formulae,

$$PSNR = 10\log 10\ (255)\ 2\ /\ MSE\ (db)$$

where MSE is the mean squared error between the original image and the reconstructed de-noised image. It is used to evaluate the different de-noising scheme like Wiener filter, Visushrink, Neighshrink, Modified Neighshrink, wavelet and multi-wavelet for all mamographic images.

8. Experiments

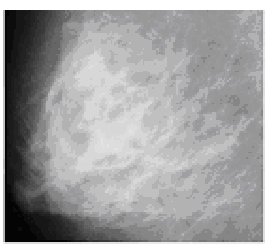
We have implemented and tested our approach on the mammograms of the MIAS database. These database images are available in reduced resolution, as compared to conventional digital mammograms. Therefore, we used only two dyadic scales in our analysis. Also, we used $G = 3$ for all images tested (different degrees of enhancement could be used, but this would make it difficult to compare the results). Next, some of our preliminary experimental results are discussed. It shall be noted that our approach can be used in mammographic images with different number of bits per pixel (e.g. contrast resolutions of 8, 12 or 16 bits/pixel). However, computational complexity increases with the number of bits per pixel, as expected.

So this paper applies the following methods for conducting experiments. One original mammographic image is applied with Gaussian noise with different variance. The methods proposed for implementing image de-noising using wavelet transform take the following forms in general. The image is transformed into the orthogonal domain by taking the wavelet transform. The detailed wavelet coefficients are modified according to the shrinkage algorithm. Finally, inverse wavelet is taken to reconstruct the de-noised image.

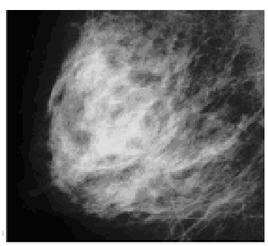
In this paper, different wavelet bases are used in all methods and multi-wavelet is applied for hard threshold. For taking the multi-wavelet transform of the image, readily available MATLAB routines are taken.

9. Results And Discussions

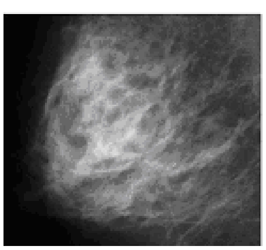
For the above mentioned Wavelet and Multi-Wavelet methods, image de-noising is performed using wavelets from the second level to fourth level decomposition and the results are shown in figure (3,4,&5) and table if formulated for second level decomposition for different noise variance as follows. It was found that three level decomposition and fourth level decomposition gave optimum results.
However, third and fourth level decomposition resulted in more blurring. The experiments were done using a window size of 3X3, 5X5 and 7X7 for Multi-Wavelet. The neighborhood window of 3X3 and 5X5 are good choices for mammographic images The images are taken from MIAS database. The experiment was also done in same mammographic window sizes for multiwavelet but multiwavelet methods produced better result than existing methods.



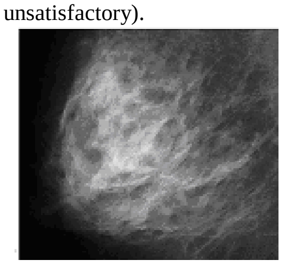
(a) original image.



(b) image enhanced by histogram equalization (local contrast in dense issues is unsatisfactory).



(c) image enhancing our contrast enhancement approach (local contrast in dense regions is improved, and the cluster of microcalcifications is more visible in the bottom right).



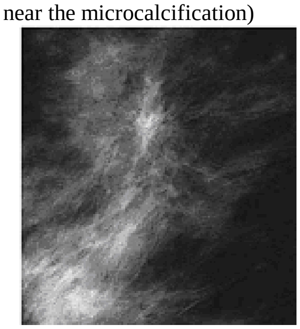
(d) image denoised and enhanced using our multiwavelet method with hard threshold (the cluster of microcalcifications is better defined in the bottom right)

Figure 3. Comparative results for the MIAS database mammogram 211, containing a cluster of microcalcifications which is not clearly visible because of the dense tissue, at the bottom right.

(a) original image.

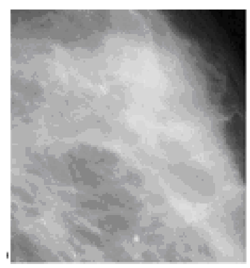
(b) image enhancement by histogram equalization (e.g. local contrast is poor in dense tissues, near the microcalcification)

(c) image contrast enhancement using our multiwavelet approach with hard threshold (showing details of the microcalcifications, including those located in dense tissue).

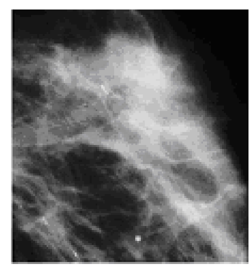


(d) image denoised and enhanced using multiwavelet (the details of the microcalcifications are visible, including those located in dense tissue).

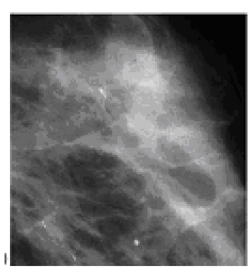
Figure 4. Comparative results for the MIAS database mammogram 148, containing microcalcifications located in dense tissue, which are not clearly visible.



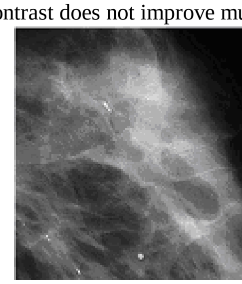
(a) original image.



(b) image enhancement by histogram equalization (local contrast does not improve much).



(c) image contrast enhancement using our multiwavelet approach with hard threshold (the boundaries of the nodule are more visible, near the image top)



(d) image denoised and enhanced using multiwavlet (the nodule boundaries are visible, near the image top).

Figure 5. Comparative results for the MIAS database mammogram 145, containing a nodule whose boundaries are not clearly visible, located near the image top.

Table 1. Comparitive Mammographic's image PSNR Values for Wavelet and Multi-Wavelet with different window sizes.

Window Size		3X3				5X5				7X7			
Wavelet	Variance	0.02	0.04	0.06	0.08	0.02	0.04	0.06	0.08	0.02	0.04	0.06	0.08
	Noisy Image	16.8601	14.1096	12.6435	11.6742	16.8309	14.0995	12.6717	11.681	16.8464	14.103	12.64	11.6592
	Wiener	24.056	21.343	19.9475	19.0223	26.4167	24.1466	22.8984	21.98	26.6335	24.8262	23.732	22.9097
Harr	Visushrink	22.2984	19.7787	18.3776	17.3849	22.2735	19.7681	18.3769	17.431	22.2856	19.807	18.332	17.4044
	Neighshrink	24.5738	23.3066	22.2924	21.5432	24.5822	23.2459	22.3749	21.555	24.5573	23.254	22.287	21.5715
	Mod.Nei	25.961	25.0158	24.1295	23.4049	25.9627	24.9922	24.2039	23.438	25.9578	24.988	24.093	23.3887
	MulWavelet	26.87	26.044	25.2441	24.966	27.189	26.733	26.1236	25.111	27.3468	26.877	25.879	25.0014
db 16	Visushrink	22.6224	20.0023	18.4513	17.5362	22.6177	19.9746	18.4704	17.506	22.6147	19.97	18.508	17.5385
	Neighshrink	23.3646	22..3845	21.5909	21.0162	23.3556	22.4143	21.6199	21.04	23.366	22.359	21.629	21.0237
	Mod.Nei	24.332	23.7027	23.0889	22.5978	24.3175	23.7657	23.1492	22.627	24.3335	23.681	23.129	22.5932
	MulWavelet	25.412	24.9421	24.6012	24.015	25.4561	24.9455	24.4588	24.104	25.4563	24.978	24.459	23.894
Sym 8	Visushrink	22.6042	19.9785	18.5036	17.4728	22.5682	19.9576	18.5172	17.517	22.6058	19.984	18.454	17.4988
	Neighshrink	23.4209	22.5088	21.6579	21.1155	23.464	22.4881	21.7373	21.053	23.4157	22.482	21.628	21.0469
	Mod.Nei	24.388	23.8718	23.2045	22.7326	24.4283	23.8263	23..2761	22.688	24.3611	23.833	23.159	22.6622
	MulWavelet	25.1334	25.146	24.4782	23.9462	25.4165	24.945	24.9687	25.136	25.2661	24.978	24.568	23.9876
Coif 5	Visushrink	22.5678	19.9391	18.5022	17.5062	22.6137	19.9899	18.4535	17.497	22.6153	19.917	18.486	17.4952
	Neighshrink	26.0778	24.2732	23.1822	22.2243	26.0365	24.3298	23.0888	22.289	26.0615	24.278	23.123	22.2693
	Mod.Nei	27.2788	26.008	25.0155	24.1331	27.2752	26.0147	24.9283	24.161	27.2978	25.981	24.999	24.1564
	MulWavelet	28.3458	27.455	26.3464	25.5781	28.3756	27.4655	26.1005	25.489	28.3201	27.0172	26.0756	25.453

10. Conclusion

In this paper, an important research challenge is to improve the visual quality of mammograms through image processing in order to detect breast cancer at an early stage. This paper describes new methods for mammographic image preprocessing for noise suppression and edge enhancement based on the wavelet transform. The image preprocessing was designed to enhance the local contrast in dense regions adaptively. The image denoising process also is adaptive and the selection of a gain factor provides the desired and detailed enhancement. Our multiwavelet approach was designed to avoid introducing artifacts in the enhancement process, which is very important when analyzing digital mammograms reliably. The preliminary results indicate that our method improves the detection of microcalcifications and other suspicious structures, even in situations where their detection is difficult (e.g. in low contrast image regions, in dense tissues), The experiments were conducted to study the suitability of different wavelet and multi-wavelet bases and also different window sizes. Experimental results also show that multi-wavelet with hard threshold gives better results than Modified Neighshrink, Neighshrink, Weiner filter and Visushrink. Compared to other approaches our method requires less user adjustment parameters. Finally, our proposed multiwavelet method has produced better mammographic screening results for physician for the early detection of breast cancer. And also the proposed method has produced best PSNR values.

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