Image Denoising using Multiscale Ridgelet for application on Mammographic image

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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. This paper purposed new multiscale ridgelet for image denoising in digital mammographic images. The performance of image denoisng algorithm in term PSNR. Finally, compares the wavelet, forst, SRAD. Our proposed methods produce the best denoised mammographic image.

*Keywords- **Multiscale Ridgelett; image Denoising; mammographic, PSNR***

1. Introduction

Digital mammography, also called full-field digital mammography (FFDM), is a mammography system in which the x-ray film is replaced by solid-state detectors that convert x-rays into electrical signals. These detectors are similar to those found in digital cameras. The electrical signals are used to produce images of the breast that can be seen on a computer screen or printed on special film similar to conventional mammograms. From the patient's point of view, having a digital mammogram is essentially the same as having a conventional film mammogram. It is a specialized form of mammography that uses digital receptors and computers instead of x-ray film to help examine breast tissue for breast cancer. Digital mammography is a NASA spin-off, utilizing technology developed for the Hubble Space Telescope. Mammography is a specific type of imaging that uses a low-dose x-ray system to examine breasts. A mammography exam, called a mammogram, is used to aid in the early detection and diagnosis of breast diseases in women. Mammography is the study of the breast using x ray. The actual test is called a mammogram. There are two types of mammograms. A screening mammogram is ordered for women who have no problems with their breasts. It consists of two x-ray views of each breast.

1.1 Breast cancer

Breast cancer is the uncontrolled growth of abnormal cells in the breast. As with other forms of cancer, breast cancer is considered to be a result of malfunctioning DNA due to damage or inherited mutation. Breast cancer is a disease that typically develops in women; however, it is also possible, although rare, for breast cancer to develop in men. According to the World Health Organization, more than 1.2 million people worldwide will learn they have breast cancer this year. The American Cancer Society estimates women in the United States will account for approximately 213,000 of these cases. The National Cancer Institute (NCI) reports breast cancer as the most common type of cancer among women in the US, second only to skin cancer [1].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 [5].the visualization of mammograms display 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 [6]. 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 The main problem of the earlier approaches that a noise estimate is needed, which may be difficult to obtain in practical situations [6], specially for images with inherent noise (e.g. X-ray images, etc In fact, the reported probabilistic approaches were not sufficiently tested for these types of images.

2 Background

Breast cancer ranks second to lung cancer as the leading cause of death in women diagnosed with cancer in the US. About 41,000 women in the US are expected to die from the disease in 2006.[2] The number of cases of women with breast cancer has been Increasing. In 2005, 211,240 women in the US were diagnosed with breast cancer, Compared to ~7,522 women in 1975, which comes out to an average increase of about 0.4% per year. However, over the last decade, due to increased awareness, screening, and improved treatments, the number of deaths due to breast cancer has been decreasing overall.[3] Figure 1.1 shows death rates due to breast cancer in comparison to other types of cancer over the last seven decades.

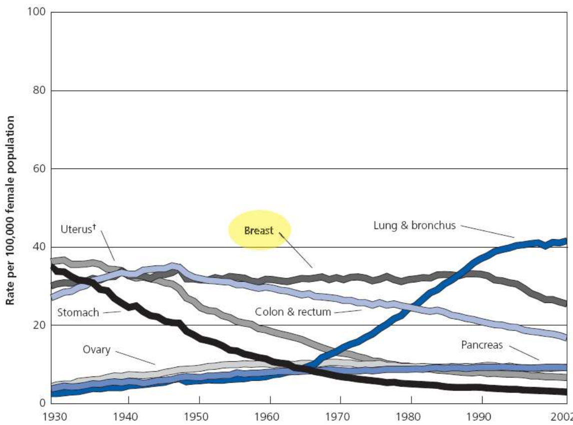

Figure 1: Age-adjusted cancer death rates of women in the US between 1930-2002.Overall, deaths due to breast cancer have been declining since 1990 yet it remains the second leading killer of women diagnosed with cancer in the US.

3. The Pre-Processing state

There mainly two domain is used to remove the noise from image is below

1. Spatial Domain
2. Transform Domain

a) Spatial Domain: These techniques are based on gray level mappings, where the type of mapping criterion chosen for enhancement .there are no. of filters that are used in spatial domain given as in spatial domain there are many filters used like Lee, forst, SRAD etc. discussed in detail below

3.1 Lee filter: Lee filter form an output image by computing a linear combination of the center pixel intensity in a filter window with the average intensity of the window. So, the filter achieves a balance straightforward averaging (in homogeneous) and the identify filter (where edges and points features exist). This balance depends on the coefficient of variation inside the moving window [7].

3.2 Frost filter: The Frost filter also strikes a balance between averaging and the all-pass filter. In this case, the balance is achieved by forming an exponentially shaped filter kernel that can vary from a basic average filter to an identity filter on a point wise, adaptive basis. Again, the response of the filter varies locally with the coefficient of variation. In case of low coefficient of variation, the filter is more average-like, and in cases of high coefficient of Variation, the filter attempts to preserve sharp features by not averaging [8].

3.3 Speckle reducing anisotropic Diffusion (SRAD):

The anisotropic diffusion technique is an extension of conventional Lee filter to suppress the speckle while preserving the edges. In this sense, the application of this extended version is applied for smoothing the medical ultrasound images in which signal-dependent, spatially correlated multiplicative noise is present

b)Transform Domain:In transform domain we will divided image into two parts high pass and low pass.there are number of transform used like wavelet, curvelet, ridgelet transform. These transform discussed below.

3.4 Wavelet based Image denoising

Wavelets are basically mathematical functions which break up the data into different frequency components, and then we study each component with a resolution matched to its scale [19]. Wavelets are the better technique to handle the different type of noises which is present in an image [11].Wavelets, although good at representing point discontinuities, are not good at representing edge discontinuities A comparative study between wavelet coefficient shrinkage filter and several standard speckle filters that are being largely used for speckle noise suppression which shows that the wavelet-based approach is deployed among the best for speckle removal [9] [10]. The wavelet decomposition of an image is done as follows: In the first level of decomposition, the image is split into 4subbands, namely the HH, HL, LH and LL sub bands as shown in Figure 2. The HH sub band gives the diagonal details of the image; the HL sub band gives the horizontal features while the LH subband represents the vertical structures[12][13]. The LL subband is the low resolution residual consisting of low frequency components and it is this subband which is further split at higher levels of decomposition [14].

3.4.1 Wavelets based noise thresholding algorithm
All the wavelet filters use wavelet thresholding operation for de-noising [17]-[20]-[21]. The basic Procedure for all thresholding method is as follows:

• Calculate the DWT of the image.
•Threshold the wavelet coefficients.(Threshold may be universal or sub band adaptive)
• Compute the IDWT to get the denoised estimate.
• There are two thresholding functions frequently used, i.e. a hard threshold, a soft threshold.

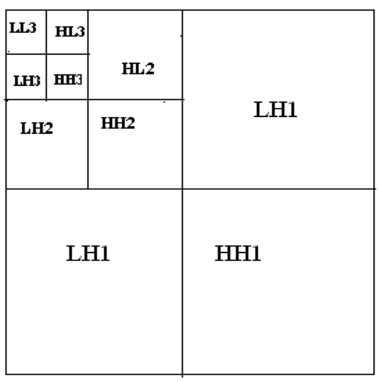

Figure 2: Decomposition of image

3.5 Ridgelet Transform (RT)

3.5.1 Radon Transform

The Radon transform of an object *f* is the collection of line integrals indexed by $(\theta,t)\in[0,2\pi)\times R$ $(\theta,t) \in [0,2\pi)$ X Rgiven by

$$Rf(\theta,t) = \int f(x_1,x_2)\delta(x_1\cos\theta + x_2\sin\theta - t)\,dx_1dx_2 \quad (1)$$

where δ is the Dirac distribution. The ridgelet coefficients $CRT_f(a,b,\theta)$ $CRT_f(a,b,\theta)$ of an object *f* are given by analysis of the Radon transform via

$$CRT_f(a,b,\theta) = \int Rf(\theta,t)a^{-1/2}\psi((t-b)/a)\,dt \quad (2)$$

Basic algorithm for discrete radon transform is as follows

1. Compute the two-dimensional Fast Fourier Transform (FFT) of function *f.*
2. Using an interpolation scheme, substitute the sampled values of the Fourier transform obtained on the square lattice with sampled values of $\hat{f}$ $\hat{f}$ on a polar lattice: that is, on a lattice where the points fall on lines through the origin.

Compute the one-dimensional Inverse Fast Fourier Transform (IFFT) on each line; i.e., for each value of the angular parameter.

3.5.2 Multiscale Ridgelet Transform (MRT)

Multiscale ridgelets based on the ridgelet transform combined with a spatial bandpass filtering operation to isolate different scales as shown in [19].

Algorithm:

1. Apply the `a trous algorithm with *J* scales [24].
2. Apply the radon transform on detail sub-bands of *J* scales.
3. Calculate ridgelet coefficients by applying 1-D wavelet transform on radon coefficients.

Get the multiscale riglet coefficients for *J* scales.

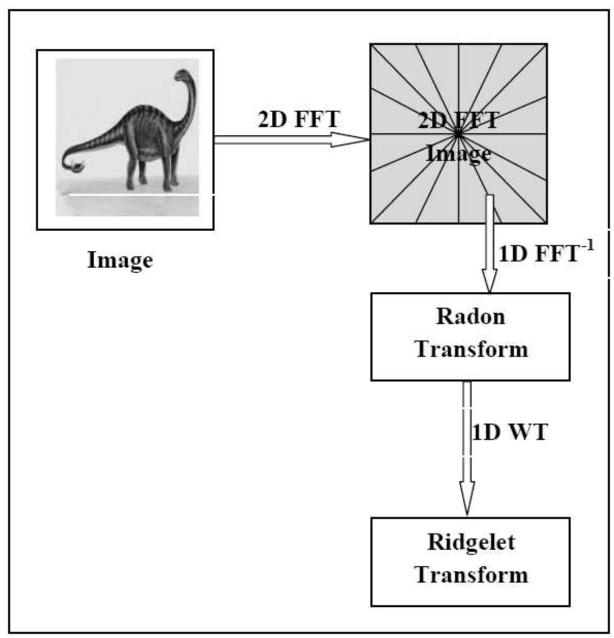

Fig. 3: Flowchart of Discrete ridgelet transform.

3.6 Image Denoising

3.6.1 Denoising by Hard Thresholding

Suppose that one is given noisy data of the form:

$$\bar{I}(x,y) = I(x,y) + \sigma Z(x,y) \quad (3)$$

Where Z(x,y) is unit-variance and zero-mean Gaussian noise. Denoising a way to recover I(x,y) from the noisy image $\bar{I}(x,y)$ as proper as possible. Rayudu et al. [18] have proposed the hard thresholds for Ultrasound image denoising as shown below:

Let y_λ be the noisy ridgelet coefficients (y = MRT*I). They used the following hard-thresholding rule for estimating the unknown ridgelet coefficients:

$$\begin{aligned} \hat{y}_\lambda &= y_\lambda; \qquad if\ |y_\lambda|/\sigma \ge k\,\tilde{\sigma}_\lambda \\ \hat{y}_\lambda &= 0\ ; \qquad else \end{aligned} \qquad (4)$$

In their experiments, they have chosen a scale dependent value for k; k = 4 for the first scale (j = 1) while k = 3 for the others (j > 1).

Algorithm:

1. Apply multiscale ridgelet transform to the noisy image and get the scaling coefficients and multiscale ridgelet coefficients.
2. Chose the threshold by Eq. (4) and apply thresholding to the multiscale ridgelet coefficients (leave the scaling coefficients alone).
3. Reconstruct the scaling coefficients and the multiscale ridgelet coefficients thresholded and get the denoised image.

3.6.2 NeighCoeff Thresholding algorithm

The hard thresholding is ineffective in many examples. Though the NeighCoeff [25] scheme which considers neighboring multiscale ridgelet coefficients to be proposed in this work. In this scheme, the size of neighbor varies with the dependence of the coefficients.

$$S^2_{j,k} = \sum_{n=-N}^{N} MRT^2_{j,k+n}; \quad N = N_0 - j \quad (5)$$

Here j is the level in curvelet decomposition and (2N+1) is the size of neighbor. N_0 can be selected according to the size of image and the support of the multiscale ridgelet coefficents:

$$MRT_{j,k} = \begin{cases} MRT_{j,k}\left(1 - \dfrac{\alpha\lambda^2}{S^2_{j,k}}\right) & if\ S^2_{j,k} \ge \alpha\lambda^2 \\ 0 & else \end{cases} \qquad (6)$$

where λ is given by *2logn* and α is a parameter that adjusts the threshold.

3.6.3 Proposed Denoising Algorithm

Algorithm:

1. Apply multiscale ridgelet transform to the noisy image and get the scaling coefficients and multiscale ridgelet coefficients.
2. Chose the threshold by Eq. (5) and (6) and apply thresholding to the multiscale ridgelet coefficients (leave the scaling coefficients alone).
3. Reconstruct the scaling coefficients and the multiscale ridgelet coefficients thresholded and get the denoised image

4. Experimental Results and Discussions

We have implemented and tested our purposed method on the mammograms image. Experiments are conducted on various test images by adding two types of noise like speckle and salt&pepper noise. The level of noise variance has also been varied after selecting the type of the noise. The PSNR from various methods are compared in table.

TABLE I DENOISING RESULTS OF VARIOUS METHODS IN TERMS OF PSNR UNDER SPECKLLE NOISE VARIANCE.

σPSNR	0.02	0.04	0.06
Frost	30.98	28.28	26.66
SRAD	35.47	36.03	35.22
Wavelet	29.67	29.46	29.18
Proposed multiscale Ridglet	38.37	37.57	36.80

TABLE II DENOISING RESULTS OF VARIOUS METHODS IN TERMS OF PSNR UNDER SALT& PEPPER NOISE 0.02 VARIANCE.

σPSNR	0.02	0.04	0.06
Frost	25.40	22.48	20.81
SRAD	24.62	19.69	16.45
Wavelet	29.44	28.84	28.01
Proposed multiscale Ridglet	37.36	34.38	31.07

5. Denoised Results

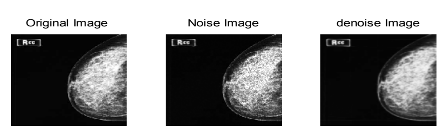

Fig 4: Denoised Image

6. Conclusion

This paper describes new methods for mammographic image preprocessing for noise based on the multiscale ridgelet. Experimental results also show with different methos. Finally, our proposed method has produced best PSNR values.

7. Future Scope

The ridgelets overcome the shortcomings of wavelets. However, the ordinary rideglet transform performs the 2-band wavelet transform in the radon domain. Therefore, it also inherits the drawback of the 2-band wavelet transform. Therefore, the ordinary ridgelet transform is not well suited for analyzing the image. So, the M-band wavelet with the ridgelet called M-band ridgelet is to be good to address this problem.

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