Noise Reduction from Mammography using Wavelets

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ABSTRACT
In the Medical image preprocessingimage denoising is a basic analysis step to provide a processed image from the raw image and it typically needs a previous application of filters to cut back the noise level of the image, whereas conserving necessary details, which can improve the standard of digital mammography images associated contribute to efficient diagnosing. From the literature, we are able to realize an outsized quantity of de-noising techniques available for various forms of images. We got some of the prevailing denoising algorithms for mammography images. Proposed work comparesseveral denoising techniques for mammographic images we tend to compare the impact of various denoising filters engaged on digitized mammograms. The considered filters are: Median, Gabor, DWT (separable, real, complex Dual-Tree) filters accustomed takes away the random noise that was added at the time of acquisition of mammography image. The results are experimented on Digital Database for Screening Mammography (DDSM) using MATLAB. The noise reduction is measured by the Root Mean Square Error (RMSE) and Peak Signal to Noise Ratio (PSNR) which illustrates the denoising capability for all methods the complex Dual-Tree DWT technique is that the best denoising technique for mammography image.

Keywords
Discrete Wavelet Transform(DWT), Complex Dual-Tree DWT, Root Mean Squared Error (RMSE), Threshold point.

1. INTRODUCTION
The most effective technique for detecting breast occult tumors is the mammography. The low contrast of the small tumors to the background, that is usually close to the noise, makes that small breast carcinoma lesions can hardly be seen within the mammography [1].In this sense, an image preprocessing to reduce the noise level of the image, preserving the mammography structures is an important item to improve the detection of mammographic features. Classically, denoising methods have been based on applying linear filters as the Wiener filter to the image, median filters, however linear methods tend to blur the edge structure of the image. Several denoising methods based on nonlinear filters have been introduced to avoid this problem [2,3,4].

The filters considered are: Median, Gabor are general methods in frequency domain, and were as DWT methods as separable, read data and complex datafiltering method are respective to the threshold point, based on asoft thresholding of the wavelet transformed coefficients of the image, and a filter based on the independent component analysis of the image [4,5,6].

The wavelet transform comes in many forms. The critically-sampled sort of the wavelet transform provides the foremost compact representation; but, it's many limitations. as an example, it lacks the shift-invariance property, which is most important in accurate denoising technique and it requires in multiple dimensions. For these reasons, it seems that for a few applications, enhancements are often obtained by victimizationassociate in nursing expansive wavelet transform in situ of a critically-sampled one

2. REVIEW OF LITERATURE
Some work has been done in the past for the enhancement of mammograms. Dhawan et al. [6] proposed an optimal adaptive neighborhood processing algorithm with a set of contrast enhancement functions to enhance the mammographic features. The method was the improvement of the earlier work developed by Gordon and Ranagayyan [6].The method can enhance the desired, but unseen or barely seen features of an image with little enhancement of the noise and other background variations. Tomklavet.al [7] proposed a new algorithm for both local contrast enhancement and background texture suppression in digital mammography images.ShihuaCai&Keyong Li [10] implemented the technique for denoising is wavelet thresholding (or "shrinkage") based in which they have implemented 2d DWT methods on gray image come up with complex dual tree DWT method.N. G. Kingsbury [8] proposed the dual-tree complex wavelet transform overcomes the limitations of linear filtering techniques- it is nearly shift-invariant and is oriented in 2D.This introduces limited redundancy and allows the transform to provide approximate shift invariance and directionally selective filters while preserving the usual properties of perfect reconstruction and computational efficiency with good well-balanced frequency responses. By the literature we found that wavelet thresholding based filtering methods gives prominent results.

3. METHODOLOGY
The basic enhancement needed in mammography is denoising, especially for dense breasts. Normal mammography image can be filtered by linear filtering techniques to get denoised image, but dense breast mammography cannot be denoised by linear filtering techniques. For those images wavelet filters are good to remove the noise from the image,we are comparing the following filters by their quality of measure such as RMSE and PSNR to find the best suited denoising technique for mammography images.

3.1 Median Filter
A median filter is a nonlinear filter is efficient in removing salt and pepper noise and Gaussian noise median tends to keep the sharpness of image edges while removing noise. The several forms of median filter the effect of the size of the window increases in median filtering noise removed effectively [13].

3.2 Gabor Filter
A Gabor filter is a linear filter whose impulse response is outlined by a harmonic function increased by a Gaussian function. Owing to the multiplication-convolution property, the Fourier transform of a Gabor filter's impulse response is

that the convolution of the Fourier transform of the harmonic function and also the Fourier transform of the Gaussian function. Gobor filters are directly associated with Gabor wavelets, since they'll be designed for number of dilations and rotations. Its impulse response is outlined by a harmonic function, increased by a Gaussian function. because of the multiplication-convolution property, the Fourier transform of a Gabor filter's impulse response is the convolution of the Fourier transform of the harmonic function and also the Fourier transform of the Gaussian function. The filter incorporates a real associated an imagined imaginary representing orthogonal directions. The two parts may be formed into a complex number or used separately [12]. The Gabor space is incredibly helpful in e.g., image processing applications like iris recognition and fingerprint recognition. Relations between activations for a selected spatial location area unit terribly distinctive between objects in an image [9]. What is more, necessary activations are extracted from the Dennis Gabor space so as to make a thin object representation.

3.3 Separable wavelet Filter

Lower resolution images are so depicted by fewer pixels and may still carry enough information to perform a recognition task. Signal decompositions in separable wavelet bases area unit computed with a separable extension of the filter bank constructs separable wavelet bases in any dimension, and explains the corresponding quick wavelet transform algorithm. This is illustrated in the diagram below. The synthesis filter bank combines the four subband images to obtain the original image of size n1 by n2 [10,13].

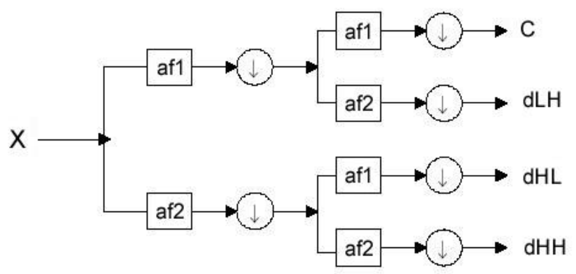

Fig 1. One stage in multi-resolution wavelet decomposition of an image.

3.4 Dual-Tree Wavelet Transform

The dual-tree DWT is enforced as two separate binaural filter banks. to achieve the benefits represented, you cannot randomly opt for the scaling and wavelet filters employed in the two trees. The lowpass (scaling) and highpass (wavelet) filters of one tree, should generate a scaling function and wavelet that square measure approximate Hilbert transforms of the scaling function and wavelet generated by the lowpass and highpass filters of the opposite tree, Therefore, the complex-valued scaling function and wavelet formed from the two trees are close to analytic.

As a result, the dual-tree (complex) DWT exhibits less shift variance and additional directional property than the critically sampled DWT with solely a redundancy issue for two-dimensional data. The redundancy within the dual-tree DWT is considerably less than the redundancy within the undecimated (stationary) DWT.

4. EXPERIMENTAL RESULTS

Among all the techniques discussed above, one technique for denoising is wavelet thresholding (complex dual tree DWT). After we decompose data victimization the wavelet transform, we use filters that act as averaging filter, et al that produce details. A number of the resulting wavelet coefficients correspond to details within the data set. If the details are small, they could be omitted while not well affecting the most features of the data set. The concept of threading is to line all high frequency sub-band coefficients that less than but a particular threshold to zero. These coefficients are utilized in an inverse wavelet transformation to reconstruct the data set [12].It has two parameters, one for noise signal and the other for threshold point. A sample noise signal is noisy image {figure 2(a)}, whose dimension is 512 x 512. We first take the forward DWT over four scales. Then a denoising methodology known as soft thresholding is applied to wavelet coefficients through all scales and subbands. Operate soft sets coefficients with values but the threshold(T) to zero, then subtracts T from the non-zero coefficients. Once soft thresholding, we take inverse wavelet transform.

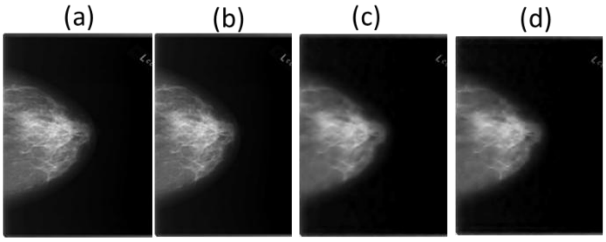

Fig. 2 Result of denoising (a) left up is original image (b) right up median filter (c) left down is separable DWT and (d) right down is Complex 2D dual-tree DWT.

We implementeddifferent methods to remove the noise from an image. These methods are Median filter, Gabor filter, separable 2-D DWT, real 2-D dual-tree DWT, and complex 2-D dual-tree DWT.The proposed method has been applied to more than 40 mammographic images from the standard Database, Digital Database for ScreeningMammography (DDSM)[14,15].

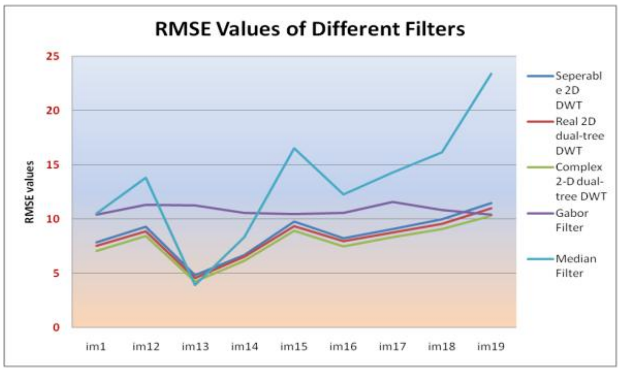

Fig4: RMSE Values

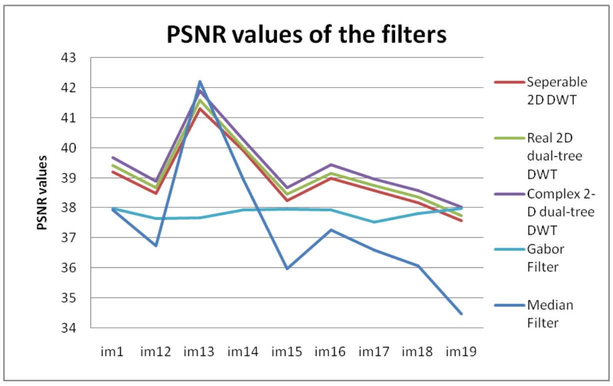

Fig 5: PSNRValues

In the figure 4 it illustrates that mimimum RMSE and figure 5 indicates that maximum PSNR is of complex 2D dual-tree DWT hance it good for denoising the mammogram images, Hower if there is a dense image it varies.

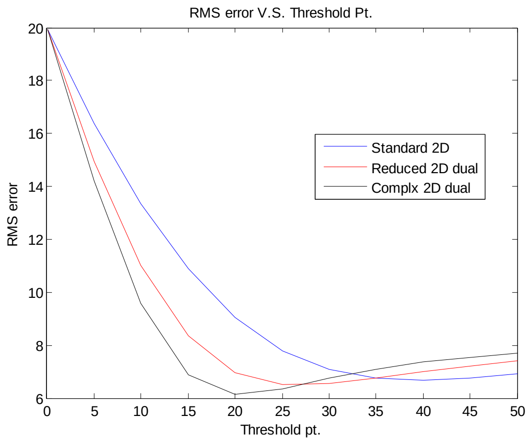

Fig 6: PSNRValues

The three method of thresholding are compared with threshold point in the Figure 8.For each method, applying the optimal threshold point yields the minimum RMS error. Therefore, a threshold producing the minimum RMS error is the optimal one. Hance the complex 2D dual tree DWT is best method for denoising the Mammogram image. Also it shows the thresholding point with respect to theRMSE.

5. CONCLUSION AND DISCUSSION

To measure the analysis of the proposed technique, we used the image quality measures such as RMSE and PSNR. The Figure 4 and Figure 5 illustrates the denoising capability of complex dual-tree technique is the most effective, followed by real dual-tree technique, separable technique, Gabor and Median filters.

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