Contourlet Transform Based Method For Medical Image Denoising

Abbas H. Hassin AlAsadi   *abbas.hassin@uobasrah.edu.iq*
Faculty of Science /Department of Computer Science
Basra University
Basra, Iraq

Abstract

Noise is an important factor of the medical image quality, because the high noise of medical imaging will not give us the useful information of the medical diagnosis. Basically, medical diagnosis is based on normal or abnormal information provided diagnose conclusion. In this paper, we proposed a denoising algorithm based on Contourlet transform for medical images. Contourlet transform is an extension of the wavelet transform in two dimensions using the multiscale and directional filter banks. The Contourlet transform has the advantages of multiscale and time-frequency-localization properties of wavelets, but also provides a high degree of directionality. For verifying the denoising performance of the Contourlet transform, two kinds of noise are added into our samples; Gaussian noise and speckle noise. Soft thresholding value for the Contourlet coefficients of noisy image is computed. Finally, the experimental results of proposed algorithm are compared with the results of wavelet transform. We found that the proposed algorithm has achieved acceptable results compared with those achieved by wavelet transform.

Keywords: Medical Image, Denoising, Wavelet Transform, Contourlet Transform.

1. INTRODUCTION

In the past decades, several non-invasive new imaging techniques have been discovered such as computerized tomography (CT) scan, single-photon emission tomography (SPET), ultrasound, digital radiography, magnetic resonance imaging (MRI), spectroscopy and others. These techniques have provided the physicians with new information about the interior of the human body that has never been available before, but for various reasons, the use of the information is very limited, and requires the use of computer technology, advanced instruments, image processing techniques, such as the elimination of the noise generated during the acquisition or transmission; enhanced contrast image; showing detail image; and so on.
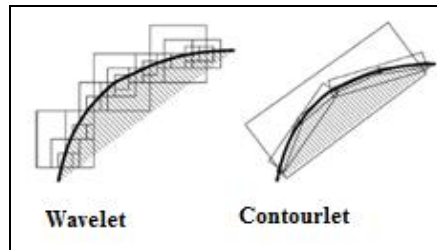
Noise is one of the medical image quality important factors. High noise of medical images may inaccuracy in the diagnosis of diseases, especially cancer diseases. It is well known that the medical diagnostic process is very important in this kind of diseases; it is mainly based normal or abnormal information provided by medical imaging to diagnose conclusion. High quality of medical images is considered the first step in the correct diagnosis, so the need to minimize the impact of noise in this kind of images.

Image Denoising is a central pre-processing step in image processing to eliminate the noise in order to strengthen and recover small details that may be hidden in the data.

The use of signal processing techniques has been recently reported by several researchers with satisfactory results. These approaches take into account the signal and noise properties in different ways.

In spite of the fact that, the Discrete Wavelet Transform (DWT) has been successfully applied for a wide range of image analysis problems. With these preferences in use, but it is recorded two observations [1]: (1) ignoring the smoothness along contours ;(2) providing only limited directional information which is an important feature of multidimensional signals [2].

Partially, these two problems have been solved by the Contourlet Transform (CT) which can efficiently approximate a smooth contour at multiple resolutions. Additionally in the frequency domain, the CT offers a multiscale and directional decomposition, providing anisotropy and directionality, features missing from the DWT [3][4] (see Figure 1). The CT has been practically used in a variety of applications, such as image denoising [5], image classification [6], image compression [7] CBIR [8], etc.
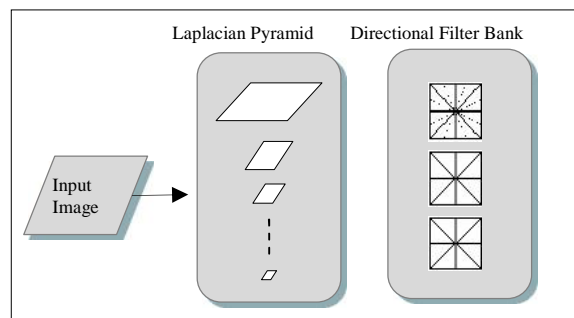

FIGURE 1: A major difference between Wavelet and Contourlet on contour representation.

2. CONTOURLET TRANSFORM BACKGROUND

The Contourlet transform has been developed to overcome the limitations of the wavelets transform [9]. It permits different and elastic number of directions at each scale, while achieving nearly critical sampling.

The Contourlet transform can be worked into two basic steps: Laplacian pyramid decomposition and directional filter banks. Firstly, the Laplacian pyramid (LP) is used to decompose the given image into a number of radial subbands, and the directional filter banks (DFB) decompose each LP detail subband into a number of directional subbands. The band pass images from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. Figure 2 shows a schematic diagram of a multilayer decomposition Contourlet.

The combination of the LP and the DFB is a double filter bank named Pyramidal Directional Filter Bank (PDFB), which decomposes images into directional subbands at multiple scales.

FIGURE 2: A schematic diagram of a multilayer decomposition Contourlet [9].

There are many research works have used CT in different applications, especially in the field of denoising and distortions of the images. Bhateja *et al.* [10] have presented a Contourlet based speckle reduction method for denoising ultrasound images of breast. In [11], authors proposed a novel method for denoising medical ultrasound images, by considering image noise content as combination of speckle noise and Gaussian noise. Fayed *et al.* [12] have presented a method for

extracting the image features using Contourlet Harris detector that is applied for medical image retrieval. Song *et al*. [13] have used scale adaptive threshold for medical ultrasound image, where in the subband Contourlet coefficients of the ultrasound images after logarithmic transform are modeled as generalized Gaussian distribution. Hiremath *et al*. [14] have proposed a method to determine the number of levels of Laplacian pyramidal decomposition, the number of directional decompositions to perform on each pyramidal level and thresholding schemes which yields optimal despeckling of medical ultrasound images, in particular. This method consists of the log transformed original ultrasound image being subjected to Contourlet transform, to obtain Contourlet coefficients. The transformed image is denoised by applying thresholding techniques on individual band pass sub bands using a Bayes shrinkage rule.

3. PROPOSED ALGORITHM

It is known that, the most common technique to remove noise from images is to transform the noisy image from the spatial domain into the frequency domain, such techniques as the Wavelet, Curvelet, and Contourlet transforms, and then compare the transform coefficients with a fixed threshold.

Typically, the low frequencies contain most of the information, which is commonly seen as a peak of data within the time-frequency domain. While, the information at the high frequencies is usually noise. The image can easily be altered within the time-frequency domain to remove the noise. Therefore, our proposed algorithm defines a new threshold value for the Contourlet coefficient to eliminate the unwanted pixels.

The Contourlet transform expression is given by,

$$ C_{j,k}^{(l)}(t) : N \sum_{i=0}^{3} \sum_{n \in Z^2} d_k^{(l)} [2n - k_i] \cap \sum_{m \in Z^2} f_i[m] W_{j>1,2n<m} \quad \cdots (1) $$

Where $C_{j,k}^{(l)}(t)$ represents the Contourlet transform of the image. The $d_k^{(l)}$ and $f_i[m]$ represents the directional filter and the band pass filter in the equation. Thus *j*, *k* and n represent the scale direction and location. Therefore *l* represents the number of directional filter bank decomposition levels at different scales *j*. Thus the output of Contourlet transform is a decomposed image coefficients.

The Laplacian pyramid at each level generates a Low pass output (LL) and a Band pass output (LH, HL, and HH). The Band pass output is then passed into directional filter bank, which results in Contourlet coefficients [15]. The Low pass output is again passed through the Laplacian pyramid [16] to obtain more coefficients and this is done till the fine details of the image are obtained. Figure 3 shows the decomposition of a given image.

3.1 Estimation of Parameters

In this section, we defined some parameters that help to determine the degree of adequacy of the proposed algorithm.

3.1.1 Optimal Threshold

Selecting the optimal threshold is a key problem for the denoising algorithms based on the threshold. The soft threshold method is selected [17]. This method is fit for image denoising based on the CT since the threshold is different for each direction of each scale. It can be described as:

$$ Sthr_{j,k} = \dagger_{j,k} * \sqrt{\frac{2\log(j+1)}{j}} \quad \cdots (2) $$

$$\dagger_{j,k} = \left(\frac{Median\left(C_{i,j}\right)}{0.6745} \right) \quad \cdots (3)$$

Where $Sthr_{j,k}$ is the threshold of kth direction of jth scale; $\dagger_{j,k}$ is the standard deviation of the noisy image; $C_{i,j}$ is the Contourlet coefficient of noisy image.

FIGURE 3: Decomposition of Contourlet Transform.

3.1.2 Noise Model
For verifying the denoising performance of the CT, two kinds of noise are added into our sample of the medical images [18]: the first is Gaussian noise; the second is speckle noise.

Gaussian noise is most commonly used as additive white noise. It is Gaussian distribution, which has a bell shaped probability distribution function given by:

$$f(x) = \frac{1}{\sqrt{2f\dagger^2}} e^{-(x-\sim)^2/2\dagger^2} \quad \cdots (4)$$

where x represents the gray level, $\sim$ is the mean of the function, and $\dagger^2$ is the standard deviation of the noise.

Speckle noise is a multiplicative noise i.e. it is direct proportion to the local grey level in any area. Speckle noise follows a gamma distribution and is given as:

$$f(x) = \frac{x^{\Gamma-1}}{(\Gamma-1)!\dagger^{\Gamma}} e^{-\frac{x}{\dagger}} \quad \cdots (5)$$

where x represents the gray level, $\dagger^2$ is the standard deviation of the noise, and $\propto$ is the shape parameter of gamma distribution.

3.1.3 Performance Criterions
The parameters which are used in estimation of performance are Signal to Noise Ratio (SNR), Mean Square Error (MSE), and Peak Signal to Noise Ratio (PSNR) [19].

Signal to Noise Ratio compares the level of desired signal to the level of background noise. The higher SNR is the lesser the noise in the image and vice versa:

$$SNR = 10\log\left(\frac{\dagger_{Org}^2}{\dagger_{Denoised}^2}\right) \quad \cdots(6)$$

Where, $\dagger_{Org}^2$ is the variance of the original image and $\dagger_{Denoised}^2$ is the variance of error between the original and denoised image.

Mean square error is given by :

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[Org(i,j) - Denoised(i,j)\right]^2 \quad \cdots(7)$$

Where, $Org(i,j)$ is the original image and $Denoised(i,j)$ is the image denoised with some filter and mn is the size of the image.

PSNR gives the ratio between possible power of a signal and the power of corrupting noise present in the image.

$$PSNR = 10\log_{10}\frac{255^2}{MSE} \quad \cdots(8)$$

Higher the PSNR gives lower the noise in the image.

3.2 Algorithm Description

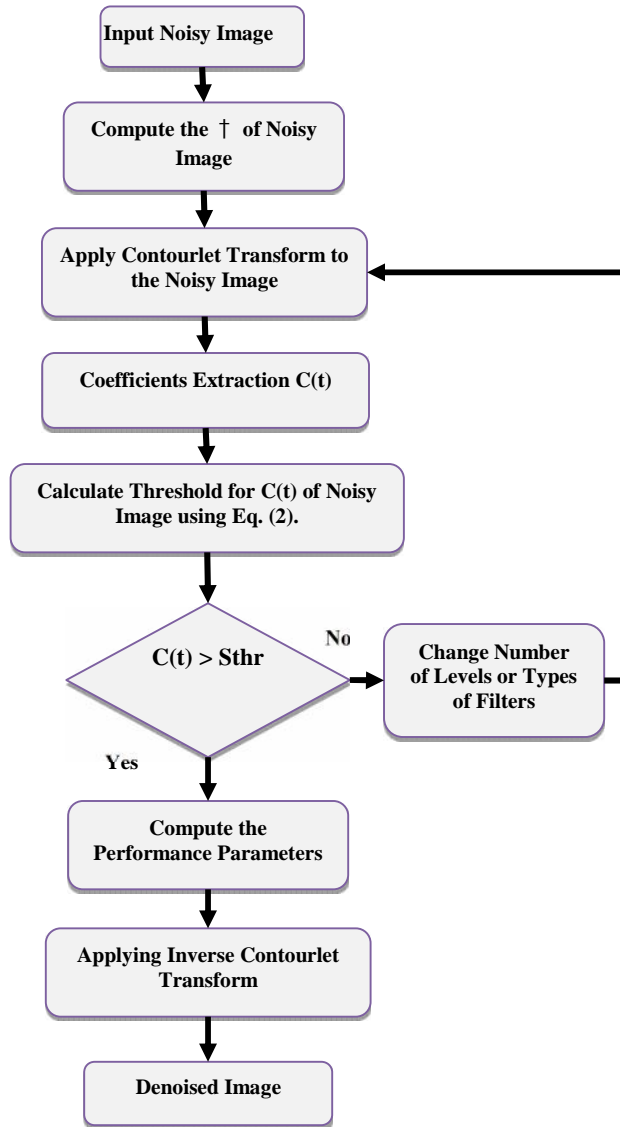The block diagram of proposed algorithm is shown in Figure 4.

FIGURE 4: Block Diagram of Proposed Algorithm.

4. RESULTS AND DISCUSSION

The proposed algorithm is applied in different medical images datasets, such as MRI, X-ray, CT scan, and ultrasound images. All images have the same size of 512×512 pixel, with 256-level grayscale.
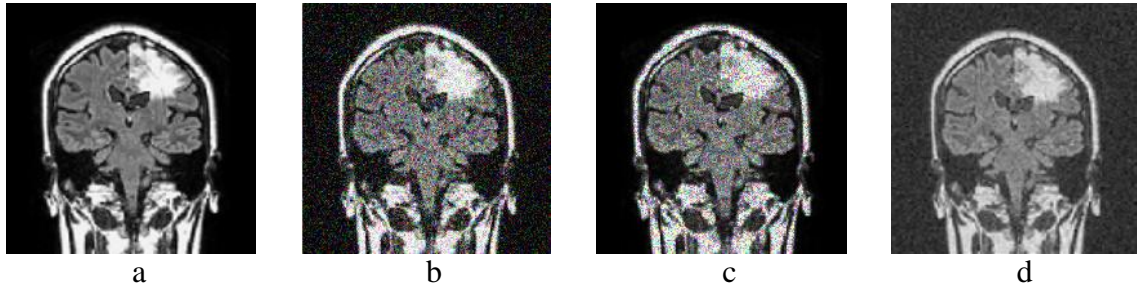
For verifying the performance of the proposed algorithm, two types of noise models are added to these images. One is an additive noise such as Gaussian noise which is given by Eq. (4); the other is a multiplicative noise i.e., speckle noise which is given by Eq. (5).

In the experimental results, the Gaussian noise with mean =0 and variance=0.03 is added to given images, while the speckle noise with noise = 0.1 is also added to the same images. For the LP stage, the 9-7 filter is used to decompose the image into 4 scales; for the DFB stage, direction
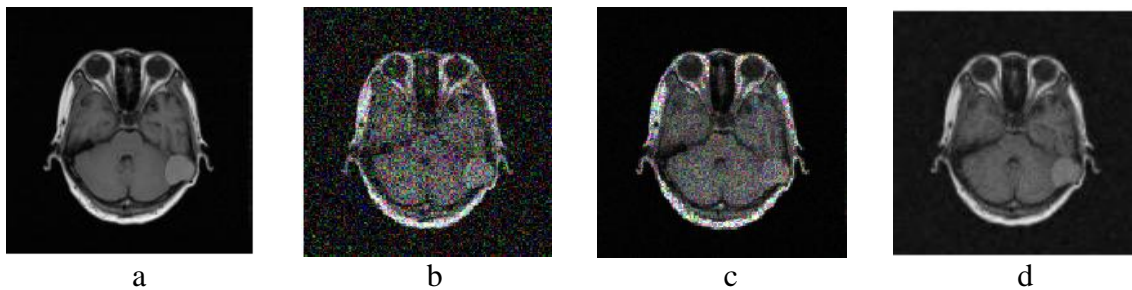
is partitioned into 3, 4, 8 and 16 directional subbands from coarse to fine scales respectively. Threshold selection is based on Eq. (2) and Eq. (3).

Figure 5 to Figure 9 show the visual results of brain MRI, CT scan, tumor MRI, ultrasound, and x-ray images after applying the proposed algorithm respectively. The performances of the proposed algorithm using PSNRs and SNRs are shown in Table 1 and Table 2 respectively.
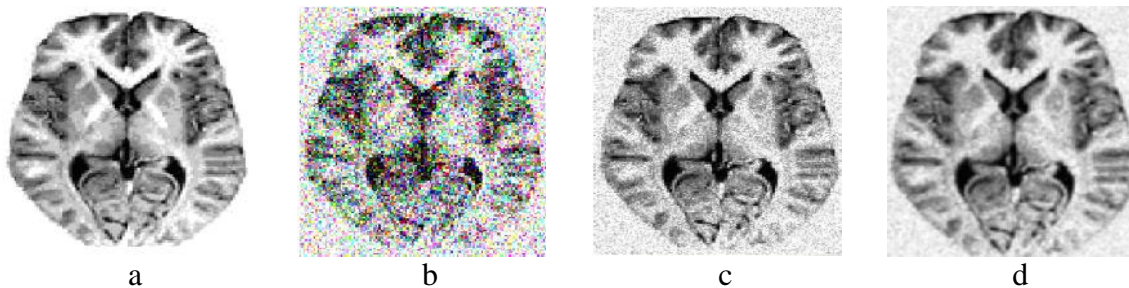
As a final point, for more judgments on the proposed algorithm in high noise levels, it is compared with the wavelet methods. The results of the comparison using PSNR and SNR are shown in Table 3 and Table 4 respectively.
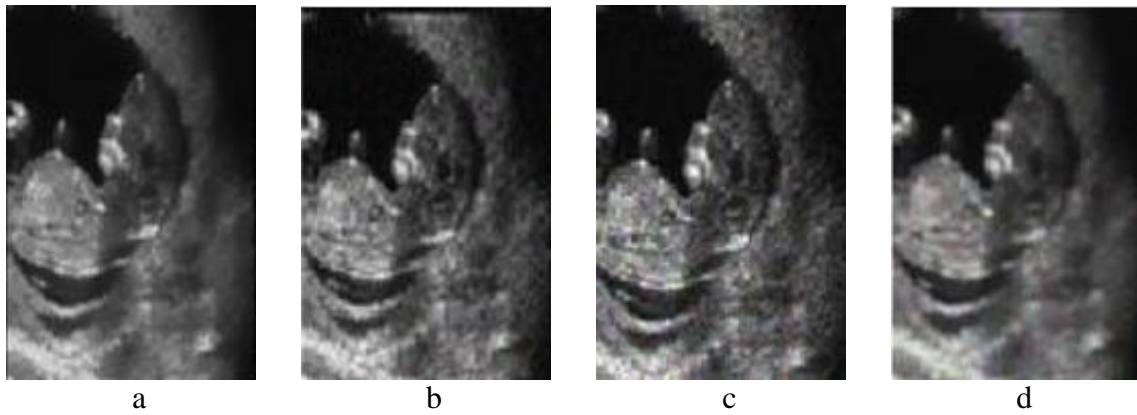

| a | b | c | d |

FIGURE 5: The visual results of brain MRI image. (a) Orignal image (b) Noisy image by Gaussian noise (c) Noisy image by speckle noise (d) Denoised image using CT.
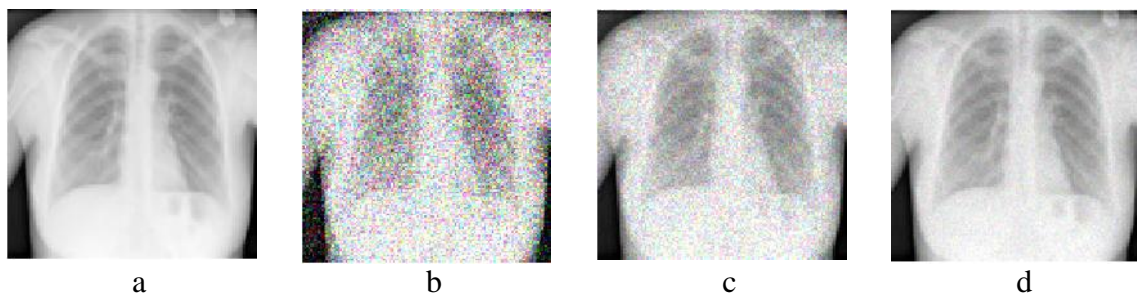

| a | b | c | d |

FIGURE 6: The visual results of CT scan image. (a) Orignal image (b) Noisy image by Gaussian noise (c) Noisy image by speckle noise (d) Denoised image using CT.

| a | b | c | d |

FIGURE 7: The visual results of tumor MRI image. (a) Orignal image (b) Noisy image by Gaussian noise (c) Noisy image by speckle noise (d) Denoised image using CT.

FIGURE 8: The visual results of ultrasound image. (a) Orignal image (b) Noisy image by Gaussian noise (c) Noisy image by speckle noise (d) Denoised image using CT.

FIGURE 9: The visual results of x-ray image. (a) Orignal image (b) Noisy image by Gaussian noise (c) Noisy image by speckle noise (d) Denoised image using CT.

Image	Noisy Image (dB)		Denoised Image by CT (dB)	
	Gaussian	Speckle	Gaussian	Speckle
Brain MRI	16.85	21.27	22.10	28.44
CT scan	14.57	17.19	19.79	26.10
Tumor MRI	7.82	12.36	13.52	18.01
Ultrasound	11.85	15.07	16.60	19.60
X-ray	16.35	18.30	20.66	22.37

TABLE 1: The PSNR value of noised and denoised images.

Image	Noisy Image (dB)		Denoised Image by CT (dB)	
	Gaussian	Speckle	Gaussian	Speckle
Brain MRI	8.65	13.96	15.79	19.22
CT scan	4.36	9.85	8.19	13.27
MRI Tumor	2.37	13.70	6.83	18.76
Ultrasound	2.26	5.83	7.37	9.52
X-ray	14.00	10.42	18.98	16.78

TABLE 2: The SNR value of noised and denoised images.

Image	Noisy Image (dB)		Denoised Image by WT (dB)		Denoised Image by CT (dB)	
	Gaussian	Speckle	Gaussian	Speckle	Gaussian	Speckle
Brain MRI	16.85	21.27	20.78	26.31	22.10	28.44
CT scan	14.57	17.19	18.49	23.97	19.79	26.10
Tumor MRI	7.82	12.36	12.21	15.98	13.52	18.01
Ultrasound	11.85	15.07	15.29	17.57	16.60	19.60
X-ray	16.35	18.30	19.34	20.29	20.66	22.37

TABLE 3: The PSNR values of the comparison between the proposed algorithm and the wavelet method.

Image	Noisy Image (dB)		Denoised Image by WT (dB)		Denoised Image by CT (dB)	
	Gaussian	Speckle	Gaussian	Speckle	Gaussian	Speckle
Brain MRI	8.65	13.96	14.47	17.09	15.79	19.22
CT scan	4.36	9.85	11.95	11.26	8.19	13.27
Tumor MRI	2.37	13.70	17.45	16.75	6.83	18.76
Ultrasound	2.26	5.83	8.22	7.74	7.37	9.52
X-ray	14.00	10.42	15.46	14.65	18.98	16.78

TABLE 4: The SNR values of the comparison between the proposed algorithm and the wavelet method.

5. CONCLUSION

High quality of medical images is considered the first step in the correct diagnosis, so the need to minimize the impact of noise in this kind of images. In this paper, an algorithm of medical image denoising based on Contourlet transform is proposed. The Contourlet transform is chosen because it is suitable for processing two-dimensional images, and also uses more directions in the transformation and can removes the noise pretty well in the smooth regions and also along the edges. We applied the algorithm in different medical images datasets. The experimental results show that this proposed algorithm performs better than the wavelet methods in both visually and statistically.

Finally, design a new filter for the directional filter banks is mentioned as a future work.

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Abbas H. Hassin AlAsadi

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