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DENOISING OF COMPUTER TOMOGRAPHY IMAGES USING CURVELET TRANSFORM

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ABSTRACT

A special member of the emerging family of multiscale geometric transforms is the curvelet transform which was developed in the last few years in an attempt to overcome inherent limitations of traditional multistage representations such as wavelets. The Computer Tomography images were denoised using both wavelet and curvelet transform and results are presented in this paper. It has been found that the cuvelet transform outperforms the wavelet transform in terms of signal noise ratio.

Keywords: denoising, wavelet, curvelet, transform, computer tomography.

INTRODUCTION

Medical images are generally of low contrast and they often have a complex type of noise due to various acquisition, transmission storage and display devices and also because of application of different types of quantization, reconstruction and enhancement algorithms. All medical images contain visual noise. The presence of noise gives an image a mottled, grainy, textured or snowy appearance. Image noise comes from a variety of sources. No imaging method is free of noise, but noise is much more prevalent in certain types of imaging procedures than in others. Nuclear images are generally the noisiest. Noise is also significant in Magnetic Resonance Imaging (MRI), Computer Tomograph (CT) and ultrasound imaging. Although noise gives an image a generally undesirable appearance, the most significant factor is that noise can cover and reduce the visibility of certain features within the image. The loss of visibility is especially significant for low-contrast objects.

Over the last decade there has been abundant interest in wavelet methods for noise removal in signals and images. The basic steps include very simple ideas like thresholding of the orthogonal wavelet coefficients of the noisy data, followed by reconstruction. Later substantial improvements in perceptual quality were obtained by translation invariant methods based on thresholding of an undecimated wavelet transform. Recently, tree-based wavelet de-noising methods were developed in the context of image de-noising, which exploit the tree structure of wavelet coefficients and the so-called parent-child correlations that are present in wavelet coefficients of images with edges. Subsequently many investigators have experimented with variations on the basic schemes, modifications of thresholding functions, level-dependent thresholding, block thresholding, adaptive choice of threshold, Bayesian conditional expectation nonlinearities and so on [1-2].

A special member of the emerging family of multiscale geometric transforms is the curvelet transform which was developed in the last few years in an attempt to overcome inherent limitations of traditional multistage representations such as wavelets. The curvelet transform, like the wavelet transform, is a multiscale transform, with frame elements indexed by scale and location parameters. The transform was designed to represent edges and other singularities along curves much more efficiently than traditional transforms, i.e. using many fewer coefficients for a given accuracy of reconstruction. Thus, in order to represent an edge to squared error 1/N requires 1/N wavelets and only about $1/\sqrt{N}$ curvelets [3-7].

This paper presents the image de-noising on different CT using both wavelet transform and curvelet transform. The performances of both the transforms are compared in terms of Peak Signal to Noise Ratio (PSNR) and the results are presented.

MATERIALS AND METHODS

CT scan images of a brain slice of ten patients were denoised using curvelet and wavelet transforms. Various types of noise like the Random noise, Gaussian noise, Salt, Pepper and speckle noise were added to these images.

- A Noise factor of 30 is used for random noise.
- In case of Gaussian white noise, the mean is 0 and variance is 0.01.
- The noise density used in case of salt and pepper noise is 0.05.
- A multiplicative noise factor of 0.04 is used in case of speckle noise.

Wrapping function [8] with a decomposition level of 8 was used for denoising the CT images using curvelet transform. Hard thresholding is applied to the coefficients after decomposition. For the coarse scale elements a value of 3*sigma is used and in case of fine scale elements a value of 4*sigma is applied and coefficients which exceed the specified level of thresholding were discarded and the remaining coefficients were used to reconstruct the image using the inverse wrapping function [8].

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In case of wavelet transform, Symmlet 8 wavelet available in Wavelab with the decomposition level of 8 was used for denoising. The thresholding values were calculated using the functions available in Wavelab and denoising of the medical images were performed.

The PSNR is the most commonly used as a measure of quality of reconstruction in image denoising. The PSNR for both noisy and denoised images were identified using the following formulae:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\|I(i,j) - K(i,j)\|^2$$

Mean Square Error (MSE) which requires two *m* x *n* grey-scale images *I* and *K* where one of the images is considered as a noisy approximation of the other is defined as:

The PSNR is defined as:

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right)$$

Here, MAX_I is the maximum pixel value of the image.

The PSNR of the images denoised is compared using wavelet and curvelet transform for each type of noise mentioned above. Then the mean and standard deviation of each noise was calculated.

RESULTS AND DISCUSSION

The CT scan image of the brain slices of ten patients containing the same four types of noises have been denoised using Curvelet and Wavelet transforms and the PSNR values were obtained for the denoised images. The outputs have been shown for the brain slice of Patient 1 in Figures 1 to 4. The PSNR values for the denoised images of 10 patients are shown in Table-1. The Mean and Standard deviation of the PSNR values of the brain slice of 10 patients containing various noises is indicated in Table-2.

For the Vertebrae CT scan image the difference between the PSNR values for Curvelet denoised and Wavelet denoised images is around 2dB and for Foetus image the difference is around 3dB for Random, Gaussian and Speckle noises. But in both these images the difference is less for Salt and Pepper noise. For Ankle and Chest images the difference in PSNR is around 4.5dB. For the Ankle image the difference is negative for the Salt and Pepper noise, and for Chest image the difference is negative for the Salt and Pepper and Speckle noises.

From Figures 5 and 6, it is obvious that the Curvelet denoised image is better than the Wavelet denoised image for the Random and Gaussain white noise cases. But for Salt and Pepper and Speckle noises present in images Wavelet denoising provides better PSNR values. From the analysis done for the denoising of the brain slices of ten patients, it was observed that there is a significant difference in PSNR values for images affected by Random and Gaussian white noises. In case of Salt and Pepper and Speckle noise in images, the Wavelet denoised images have high PSNR values than the Curvelet denoised images. For the images containing Speckle noise, the Wavelet denoised images have PSNR values around 40dB.

The Mean and Standard deviation of the PSNR values for the ten patients show that the mean PSNR value for the Curvelet denoised brain slice image that contained Random noise is 19.28 and for Wavelet denoised image it is 14.30, and the corresponding Standard deviations are 1.84 and 1.24. Similarly these values have been obtained for the other noises too. The Standard deviation is low for images affected with Salt and Pepper noise and is very high for Speckle noise.

From the analysis done we have found that denoising using the Curvelet transform recovers the original image from the noisy one using lesser coefficients than denoising using the Wavelet transform. The Wrapping based Curvelet transform technique was found to be conceptually simpler, faster and far less redundant than the existing techniques. This technique was found to be invertible with the rapid inversion algorithm of the same complexity.

In all cases it was found that the Curvelet transform outperforms the Wavelet transform in terms of PSNR and the Curvelet denoised images appear visually more pleasant than the Wavelet denoised images. The Curvelet transform provides high PSNR values and can remove the Random and Gaussian white noises from medical images very efficiently than the Wavelet transform. The Curvelet transform does not effectively remove the Salt and Pepper noise and Speckle noise from the medical images, and so Curvelet transform is not suited for removal of these two noises though it recovers the curves and edges perfectly.

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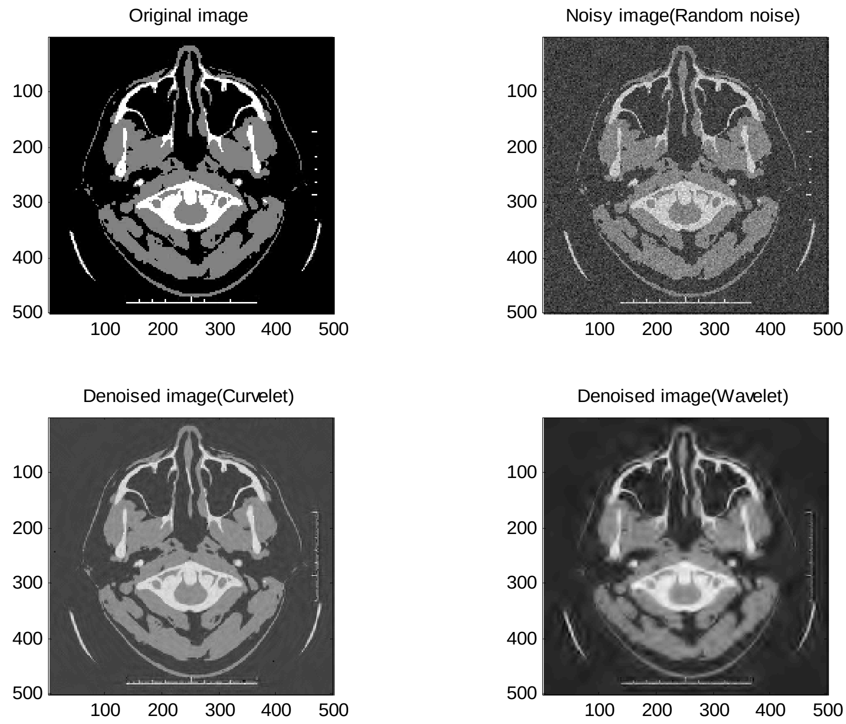
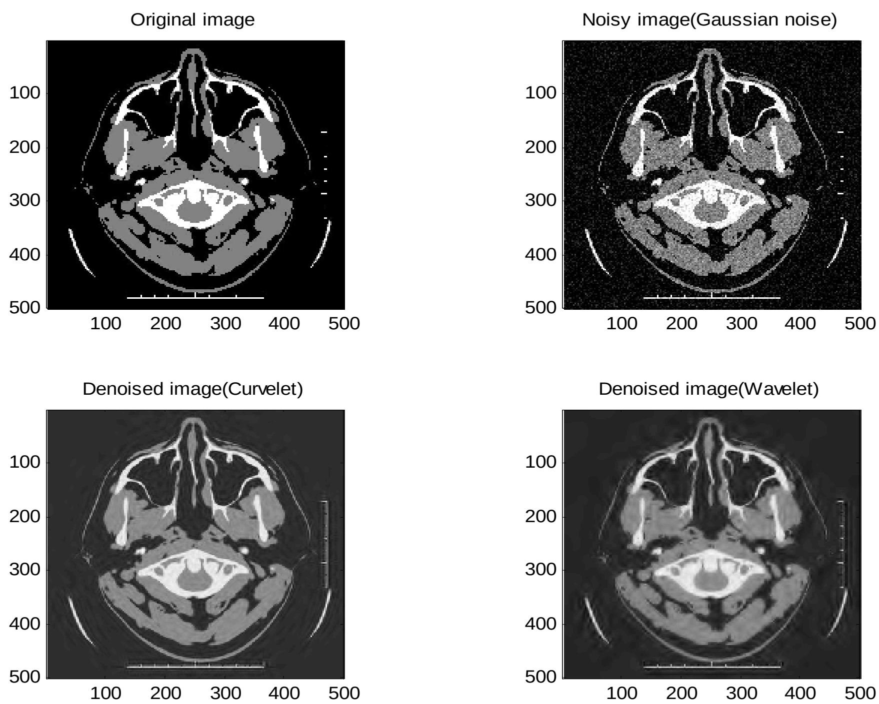


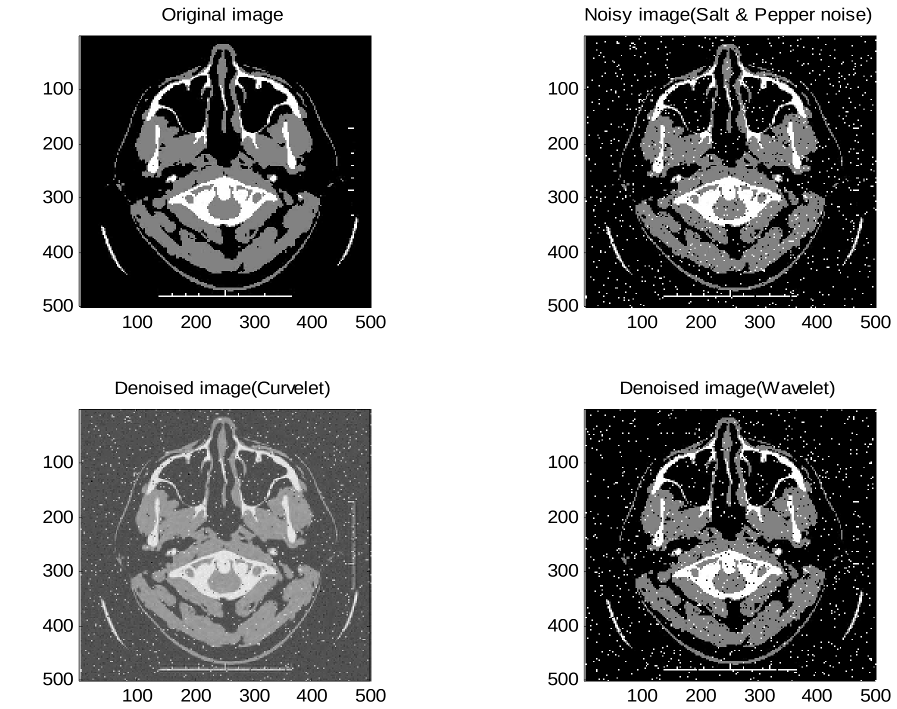
PSNR = 17.17 PSNR = 12.85

Figure-1. Denoising of a CT scan image of Patient 1 with Random noise.



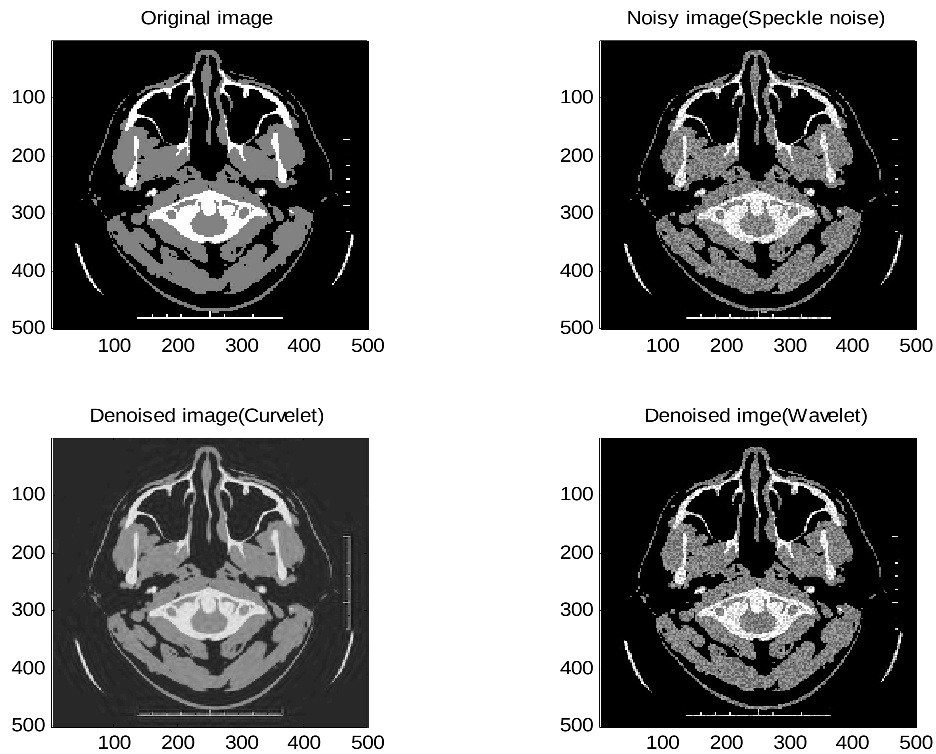
PSNR = 14.04 PSNR = 12.14

Figure-2. Denoising of a CT scan image of Patient 1 with Gaussian noise.



PSNR = 13.73 PSNR = 16.06

Figure-3. Denoising of a CT scan image of Patient 1 with Salt and Pepper noise.



PSNR = 17.28 PSNR =43.87

Figure-4. Denoising of a CT scan image of Patient 1 with Speckle noise.

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Table-1. PSNR values for denoised CT scan images.

Patient	Noise	Curvelet denoised image PSNR(dB)	Wavelet denoised image PSNR(dB)	Difference (dB)
1.	Random noise	17.17	12.85	4.32
	Gaussian noise	14.04	12.14	1.90
	Salt & Pepper noise	13.73	16.06	-2.33
	Speckle noise	17.28	43.87	-26.59
2.	Random noise	17.17	12.88	4.29
	Gaussian noise	13.88	11.96	1.92
	Salt & Pepper noise	13.65	15.98	-2.33
	Speckle noise	17.40	43.76	-26.36
3.	Random noise	20.98	15.08	5.90
	Gaussian noise	16.21	14.02	2.19
	Salt & Pepper noise	15.11	16.08	-0.97
	Speckle noise	21.74	31.67	-9.93
4.	Random noise	20.33	15.70	4.63
	Gaussian noise	15.58	14.06	1.52
	Salt & Pepper noise	14.67	15.95	-1.28
	Speckle noise	20.48	47.63	-27.15
5.	Random noise	20.10	14.29	5.81
	Gaussian noise	15.76	13.37	2.39
	Salt & Pepper noise	14.75	16.04	-1.29
	Speckle noise	20.55	33.44	-12.89
6.	Random noise	20.83	14.72	6.11
	Gaussian noise	16.11	13.81	2.30
	Salt & Pepper noise	14.99	16.13	-1.14
	Speckle noise	21.57	31.29	-9.72
7.	Random noise	18.39	13.82	4.57
	Gaussian noise	14.82	12.85	1.97
	Salt & Pepper noise	14.32	15.98	-1.66
	Speckle noise	18.54	45.11	-26.57
8.	Random noise	17.25	12.72	4.53
	Gaussian noise	13.98	11.97	2.01
	Salt & Pepper noise	13.67	16.06	-2.39
	Speckle noise	17.45	44.09	-26.64
9.	Random noise	18.18	13.52	4.66
	Gaussian noise	14.59	12.72	1.87
	Salt & Pepper noise	14.10	16.10	-2.00
	Speckle noise	18.29	45.00	-26.71
10.	Random noise	22.31	15.83	6.48
	Gaussian noise	16.65	14.32	2.33
	Salt & Pepper noise	15.30	16.13	-0.83
	Speckle noise	23.17	29.66	-6.49

Table-2. Mean and Standard Deviation.

Noise	Mean		Standard Deviation	
	CvT	WT	CvT	WT
Random noise	17.27	14.14	2.81	1.17
Gaussian noise	15.16	13.12	1.03	0.91
Salt & Pepper noise	14.43	16.05	0.62	0.06
Speckle noise	19.65	39.55	21.12	7.06

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