



Medical Image Denoising Using M-Band Ridgelet Transform with NeighCoeff Thresholding

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Abstract: In this paper, a novel image denoising algorithm using M-band ridgelet transform for medical image denoising. Also a novel threshold algorithm called NeighCoeff thresholding is used for denoising. The performance of the proposed method is tested on ultrasound and magnetic resonance imaging (MRI) image under salt and pepper noise conditions. The performance of the proposed method is compared with the existing wavelet, ridgelet and curvelet transform in terms of peak-signal to noise ratio (PSNR) and mean square error (MSE). The results after investigation proposed method shows a significant improvement in terms of PSNR and MSE as compared to other existing denoising algorithms on ultrasound and MRI images.

Keywords: Image Denoising, M-band Ridgelet Transform, Ultrasound Images, MRI Images, Curvelet.

I. Introduction

Image denoising is an active research in ultrasound imaging, magnetic resonance imaging, computer tomography as well as in areas of research and technology. Ultrasound imaging has become a popular imaging modality as it is noninvasive, portable, safe, relatively inexpensive, and provides a real-time image formation. The imaging process in ultrasound imaging is based on the principle of reflection of sound waves [19]. In ultrasound imaging a high frequency pulse of acoustic energy is emitted by a transducer. This energy interacts with the human body organs and a part of this energy is transmitted back to the transducer to be detected [20].

II. Literature Review

Jong-Sen Lee [1] has proposed the computational techniques involving contrast enhancement and noise filtering on two-dimensional image arrays are developed based on their local mean and variance. Frost et al [2] have proposed the standard image processing techniques which are used to enhance non-coherent optically produced images are not applicable to radar images due to the coherent nature of the radar imaging process. Windyga [3] has proposed a generic n-dimensional filter with the primary purpose of eliminating impulsive-like noise is presented. This recursive nonlinear filter is composed of two conditional rules, which are applied independently, in any order, one after the other. Starck et al. [5] have proposed the radon, ridgelet and curvelet transforms for image denoising. They apply these digital transforms to the denoising of some standard images embedded in white noise[4]. The simple thresholding of the curvelet coefficients is very competitive with "state of the art" techniques based on wavelets, including thresholding of decimated or undecimated wavelet transforms[17] and also including tree-based Bayesian posterior mean methods. Starck et al. have proposed a method for contrast enhancement based on the curvelet transform. The curvelet transform represents edges better than wavelets, and is therefore well-suited for multiscale edge enhancement [6].

Zliaig and Ni [7] have purposed the curvelet transform which offers exact reconstruction and low redundancy. The improved the finite ridgelet transform by means of frequency lapped orthogonal transform. The purposed curvlet transform uses FRIT as central step, and implements curvelets subbands with a combined wavelets filter bank. Abrial et al. [8] have proposed the multiscale decomposition for data on the sphere, namely the curvelet transform on the sphere. The curvelet transform, in its first step, requires the use of an isotropic wavelet transform. Therefore, our new curvelet transform also includes a new wavelet transform on the sphere which has properties similar to those of the `a trous isotropic wavelet transform.

Boubchir et al. [9] have proposed a novel nonparametric Bayesian estimator for signal and image denoising in the wavelet domain. This approach uses a prior model of the wavelet coefficients designed to capture the sparseness of the wavelet expansion. Ho et al. [10] have proposed the Wavelet Bayesian Network Image Denoising. Their approach exploits a hidden Bayesian network, constructed from wavelet coefficients, to model the prior probability of the original image. Fathi et al. [11] have proposed the statistically optimum adaptive wavelet packet (WP) thresholding function for image denoising based on the generalized Gaussian distribution.

The ridgelets[18] overcome the shortcomings of wavelets. However, the ordinary ridgelet transform performs the 2-band wavelet transform in the radon domain. Therefore, it also inherits the drawback of the 2-band wavelet transform. Thus a high frequency channels have wide bandwidth and low frequency channels have narrow

bandwidth[20]. These characteristics are suitable for analyzing low frequency signal, but not for relatively high frequency signal. The images often contain many edges, which may cause rich middle and high frequency components in the radon domain. Therefore, the ordinary ridgelet transform is not well suited for analyzing the image. In this paper, the M-band wavelet with the ridgelet called M-band ridgelet [12] is proposed to address the image denoising problem.

III. Ridgelet Transform

A. Radon Transform

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

$$R_y(\theta, t) = \int y(x_1, x_2) \delta(x_1 \cos \theta + x_2 \sin \theta - t) dx_1 dx_2 \quad (1)$$

where δ is the Dirac distribution. The ridgelet coefficients $CRT_y(a, b, \theta)$ of an object y are given by analysis of the Radon transform as

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

B. Discrete Ridgelet Transform (DRT)

A continuous ridgelet transform is calculated by applying one dimensional wavelet transform to the slices of radon transform $R_y(\theta, \cdot)$. Radon transform uses a projection-slice theorem

$$\hat{f}(\omega \cos \theta, \omega \sin \theta) = \int R_y(\theta, t) e^{-2\pi i \omega t} dt \quad (3)$$

According to the theorem Radon transform can be obtained by applying the one-dimensional inverse Fourier transform to the two-dimensional Fourier transform of function restricted to radial lines through the origin. For the ridgelet transform, apply a one-dimensional wavelet transform along the radial variable in Radon space. The DRT of an image of size $n \times n$ is an image of size $2n \times 2n$, introducing a redundancy factor equal to 4 [5].

C. M-band Ridgelet Transform (MRT)

M-band ridgelet is based on the ridgelet transform which is combined with a M-band wavelets has been proposed in this paper for image denoising. Fig. 1 illustrates the flowchart for the digital implementation of proposed M-Band ridgelet transform

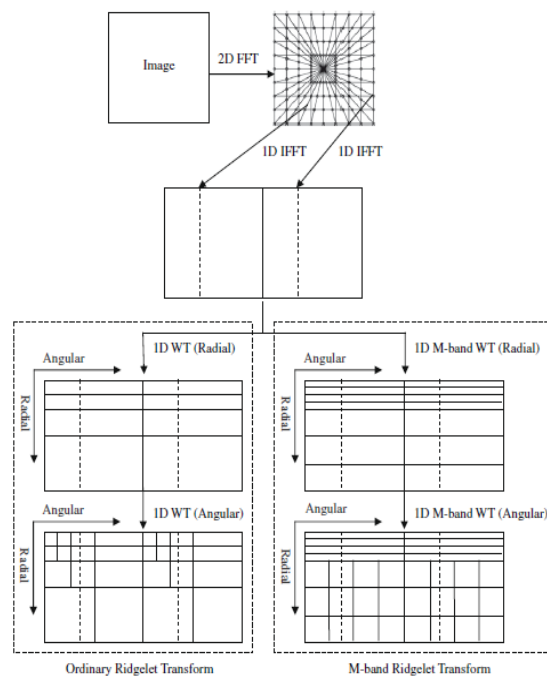


Figure 1: Flowchart of Ridgelet and M-Band ridgelet transform [12]

IV. Image Denoising

A. Denoising by Hard Thresholding

There is given noisy data of the form:

$$I(x,y)=I(x,y)+\sigma Z(x,y) \quad (4)$$

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. [13] 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:

$$\begin{aligned} \hat{y}_\lambda &= y_\lambda; & \text{if } |y_\lambda|/\sigma \geq k \tilde{\sigma}_\lambda \\ \hat{y}_\lambda &= 0; & \text{else} \end{aligned} \quad (5)$$

B. NeighCoeff Thresholding algorithm

The hard Thresholding may not be always effective in many examples. The NeighCoeff [14] scheme considers neighboring M-band ridgelet coefficients in this paper. The size of neighbor varies with the dependence of the coefficients.

$$S_{j,k}^2 = \sum_{n=-N}^N MRT_{j,k+n}^2; \quad N = N_0 - j \quad (6)$$

Here j is the level in the 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 M-band ridgelet coefficients:

$$MRT_{j,k} = \begin{cases} MRT_{j,k} \left(1 - \frac{\alpha \lambda^2}{S_{j,k}^2} \right) & \text{if } S_{j,k}^2 \geq \alpha \lambda^2 \\ 0 & \text{else} \end{cases} \quad (7)$$

where λ is given by $2 \log n$ and α is a parameter that adjusts the threshold.

V. Experimental Results and Discussions

Removal of noises from the images is a critical issue in the field of digital image processing. The phrase peak signal to noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupted noise that affects the fidelity of its representation. The evaluation measures, PSNR and mean square error (MSE) are defined as follows:

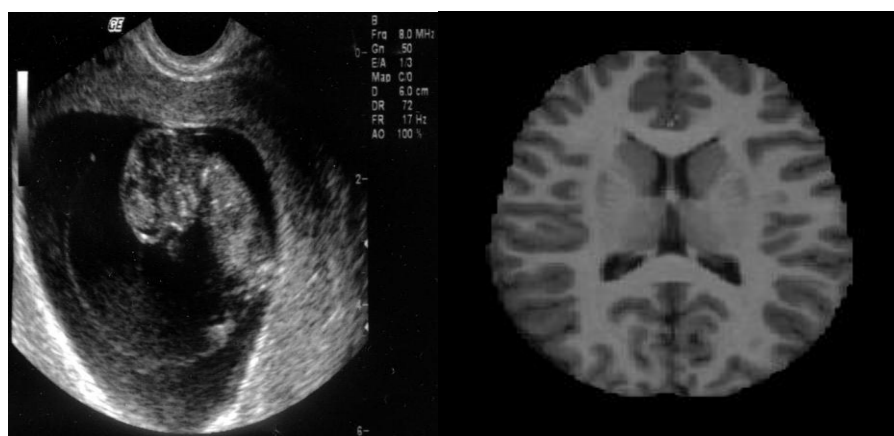
$$PSNR = 20 \log_{10} \left(\frac{255}{MSE} \right) \quad (8)$$

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \|I(i, j) - k(i, j)\|^2 \quad (9)$$

Table 1 Denoising results of Ultrasound image under Salt & Pepper noise density varying from 0.01 to 0.1

Noise Density	Wavelet		Ridgelet		Curvelet		M-Band Ridgelet	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
0.01	23.826	19.934	25.059	14.242	28.929	9.122	29.081	8.963
0.02	22.476	25.389	23.390	17.258	27.602	10.627	28.526	9.555
0.03	20.871	29.624	22.120	19.976	26.481	12.092	27.957	10.202
0.04	20.010	33.360	21.158	22.316	25.581	13.412	27.387	10.897
0.05	19.060	37.240	20.359	24.468	24.737	14.781	26.774	11.690
0.06	18.848	40.125	19.687	26.435	24.017	16.058	26.139	12.577
0.07	17.613	43.232	19.208	27.939	23.487	17.069	25.669	13.276
0.08	17.521	45.821	18.536	30.182	22.719	18.645	24.934	14.448
0.09	16.681	48.689	18.087	31.781	22.227	19.732	24.459	15.261
0.1	16.347	51.555	17.728	33.122	21.767	20.807	23.992	16.104

Fig 2 shows the sample images under influence of Salt & Pepper noise on which Wavelet, Ridgelet, Curvelet and M-Band Ridgelet transform is applied. Table 1 illustrates the denoising results of various methods on ultrasound sample image US1 under Salt & Pepper with noise density varying from 0.01 to 0.1. In Fig 3 and Fig 4 comparison is shown for PSNR and MSE value for Wavelet, Ridgelet, Curvelet and M-Band Ridgelet. It is clear from the graphs that the proposed method M-Band Ridgelet shows a significant improvement in PSNR and MSE as compared to Wavelet, ridgelet and curvelet transform.



(a) (b)

Figure 2: Sample Images (a) Ultrasound Image (b) MRI image

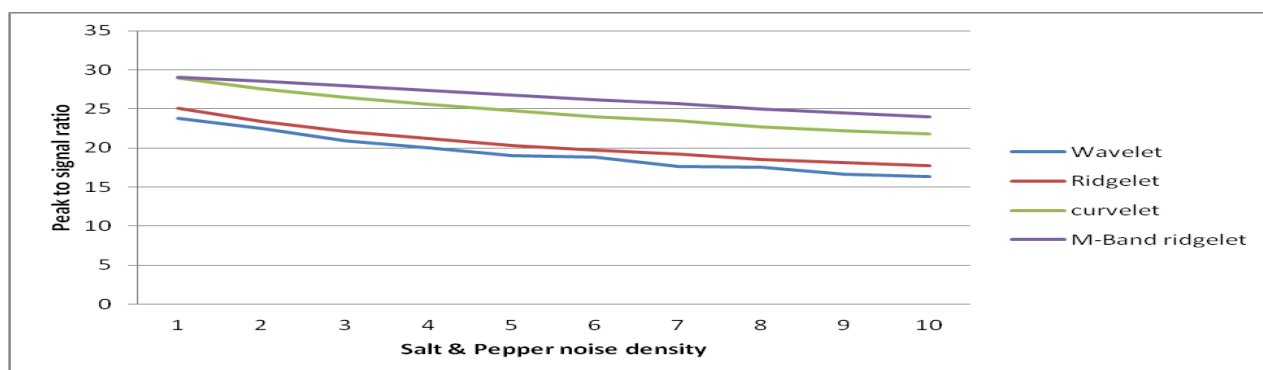


Figure 3: Graphical results for ultrasound image PSNR values

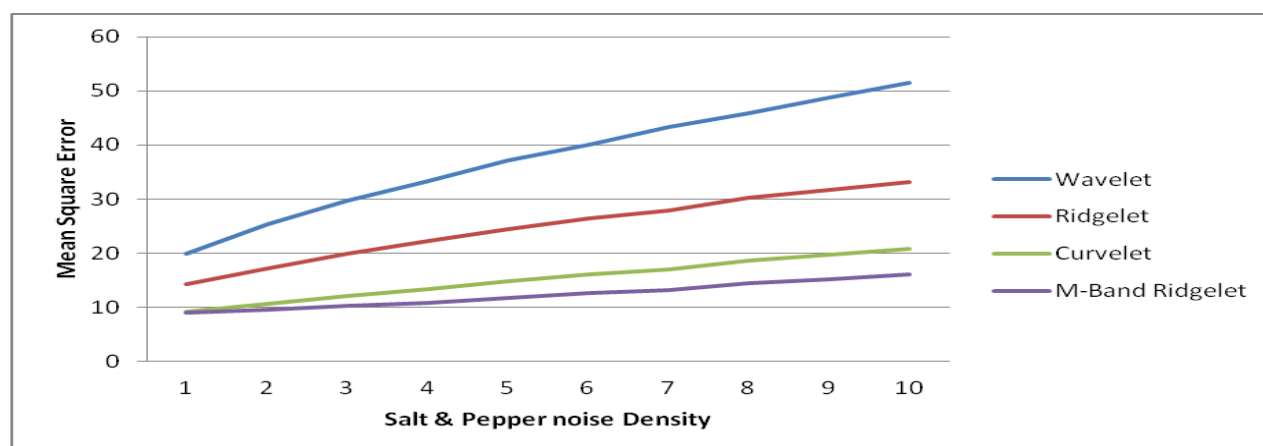


Figure 4: Graphical results for ultrasound image MSE values

Table 2 Denoising results of MRI image under Salt & Pepper noise density varying from 0.01 to 0.1

Noise Density	Wavelet		Ridgelet		Curvelet		M-Band Ridgelet	
	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE
0.01	24.585	16.325	25.353	10.636	28.279	6.284	29.203	4.644
0.02	21.821	23.251	23.409	14.250	25.893	8.169	27.929	5.539
0.03	20.378	27.628	22.473	17.150	24.743	9.788	26.815	6.434
0.04	19.151	31.847	21.293	19.732	23.629	11.261	25.467	7.354
0.05	18.469	35.322	20.459	22.385	22.440	12.987	24.446	8.511
0.06	17.437	38.643	19.699	24.534	21.589	14.324	23.324	9.480
0.07	16.788	41.908	19.254	26.589	21.493	15.747	22.694	10.633
0.08	16.327	44.497	18.811	28.322	20.697	16.889	22.160	11.542
0.09	16.062	47.439	18.409	30.624	20.501	18.690	21.297	13.092
0.1	15.397	49.674	18.011	32.031	19.325	19.671	20.708	13.826

Table 2 illustrate the denoising results of various methods on MRI [15] sample image under Salt & Pepper with noise density varying from 0.01 to 0.1. Fig. 5 and Fig 6 graphically show the results for Wavelet, Ridgelet, Curvelet and M-Band Ridgelet transform for PSNR and MSE. It is clear that the proposed method M-Band Ridgelet shows a significant improvement in terms of PSNR and MSE as compared to wavelet, ridgelet and curvelet transform.

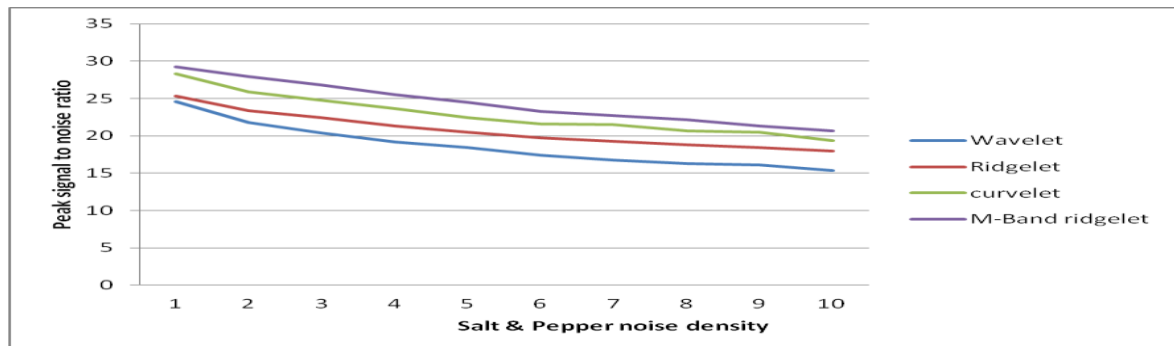


Figure 5: Graphical results for MRI image PSNR values

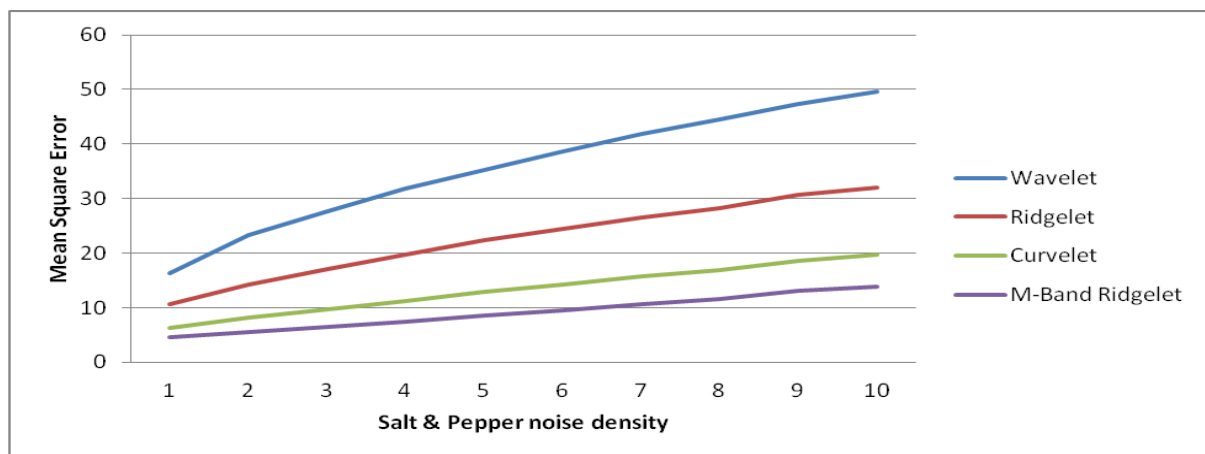


Figure 6: Graphical results for MRI image MSE values

VI. Conclusion

The ridgelet transform with M-band wavelet transform called M-band ridgelet transform is proposed in this paper for image denoising. The performance of the proposed method is tested on ultrasound and MRI image under salt & pepper noise. The results of the proposed method is compared with the wavelet, ridgelet and curvelet transform in terms of PSNR and MSE. The results after being investigated shows a significant improvements compared to the wavelet, ridgelet and curvelet denoising algorithms.

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