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Image De-noising Using Wavelet-Like Transform

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Abstract

This paper proposes a comparative study of image denoising method using BlockShrink algorithm between the Wavelet transform (DWT) and the Slantlet transform (SLT). Slantlet transform, which is also a wavelet-like transform and a better candidate for signal compression compared to the DWT based scheme and which can provide better time localization. BlockShrink is found to be a better method than other conventional image denoising methods. Through experimental results, it is found that DWT based BlockShrink thresholding is better option than BiShrink thresholding in terms of PSNR for the Gaussian noise. The PSNR for the SLT based BlockShrink, though found to be less than DWT based method, is better option as it provides better time localization and better signal compression compared to the classical DWT.

1. Introduction

Image denoising is usually the first essential step in image analysis. There are number of applications such as biomedical engineering, forensic science etc. where the tasks of feature extraction and object recognition become difficult if the images are corrupted with noise. The most important point in developing image denoising algorithm for Medical diagnosis operations is that the fine details in a medical image embedding diagnostic information should not be destroyed during noise removal. In fact, algorithm should enhance and recover fine details that may be hidden in the data. There are usually three basic approaches to image denoising – Spatial Filtering, Transform Domain Filtering and Wavelet Thresholding Method [13-15]..

Wavelet thresholding method depends on the choice of a thresholding parameter. It removes noise by removing coefficients that are irrelevant relative to threshold. There are several studies on thresholding the Wavelet coefficients [7]. However, Wavelet based denoising algorithms suffers from shift variance and lack of directionality. To overcome this problem, the researchers have used contourlets and complex dual tree wavelet transform to eliminate the noise from the noisy image [10-11].

There are various thresholding techniques which are used for purpose of image denoising such as hard thresholding, soft thresholding, affine thresholding, VisuShrink, SureShrink , BayesShrink, BiShrink and NormalShrink [3-6,12].

Z. Dengwen and S. Xiaoliu [2] have proposed a new image denoising method BlockShrink. BlockShrink is a completely data-driven block thresholding approach. The authors have observed that Block Shrink outperforms significantly classic SureShrink method and NeighShrink method[9]. This method utilizes the pertinence of the neighbour wavelet coefficients by using the block thresholding scheme. It can decide the optimal block size and threshold for every wavelet subband by minimizing Stein's unbiased risk estimate (SURE).

BlockShrink Algorithm [2]

1.Suppose an image X = {Xij} is contaminated with Gaussian random noise with zero mean and variance σ2. The noisy image Y is observed as

$Y_{ij} = X_{ij} + \epsilon_{ij} \quad i,\ j = 1, \ldots, N$

where N is some integer power of 2 and $\epsilon = \{\epsilon_{ij}\}$ is independent and identically Gaussian (normal) distributed (iid) $N(0, \sigma^2)$.

2. An J-level 2-D orthogonal wavelet transform **W** is performed on a noisy image **Y =** $\{Y_{ij}\}$, to generate several subbands LL_j, HL_j, LH_j and HH_j, respectively

3. Every detail subband is thresholded (except the LL_j subband).

4. Then, search the optimal threshold λ^s and block size L^S by

$(\lambda^s , L^S) = \text{argmin SURE } (w ,\lambda , L^2)$

where λ^s is one of all $\{S^2_{n\,xm}\}$ on the subband and

$S^2_{n\,xm} = \sum\sum w_{ij}$, (i ϵ A={ i : (n-1)L +1 <=i <= nL};
j ϵ B={ j : (m-1)L +1 <=j <= mL.}).

5. Also, limit the block size search range to be
$1 \le L \le \lceil (N / 2^k)^{3/4}$.

6. Next, obtain the estimate θ* of the noiseless wavelet coefficients w by

$\theta^*_{ij} = w_{ij} (1 – \lambda/ S^2_{n\,xm})$ where i ϵ A and j ϵ B.

7. Finally apply Inverse Wavelet transform on the modified coefficients to obtain the denoised estimate, $W^* = \mathbf{W^{-1}\theta^*}$.

This study presents a comparative study of image denoising based on wavelet and wavelet-like transforms using the BlockShrink thresholding method with the Selesnick Wavelet based Bivariate Shrink approach. In the subsequent secion, we briefly discuss of the slantlet transform. In section 3, we present the experimental results with analysis.

2.Slantlet Transform

Slantlet transform (SLT) is an orthogonal discrete wavelet transform with approximation order two, i.e., with two zero moments and improved time localization. It was introduced by Ivan W. Selesnick [14] in 1999.

It uses a special case of a class of bases described by B. Alpert et al. [1], the construction of which relies on Gram-Schmidt orthogonalization. It is based on a filterbank structure, implementing in a parallel form, employing different filters for each scale.

In DWT, some of these parallel branches employ product of basic filters whereas in SLT, the Slantlet filter branches do not employ any product form of implementation, as shown in figure 1 and hence ST possesses extra degrees of freedom.

Ivan W. Selesnick [14] has shown that due to this property, SLT can be implemented employing filters of shorter supports, and yet maintaining the desirable characteristics like orhtogonality and an octave-band characteristics, with two zero moments. Though SLT has no tree structure like DWT, it can be efficiently implemented with same order of complexities as of DWT.

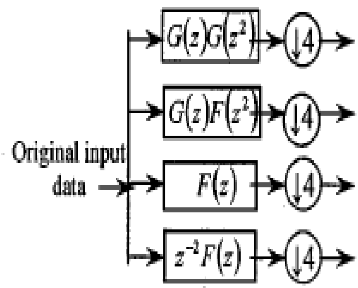

Fig.1: (a) Two-scale iterated filterbank using the DWT

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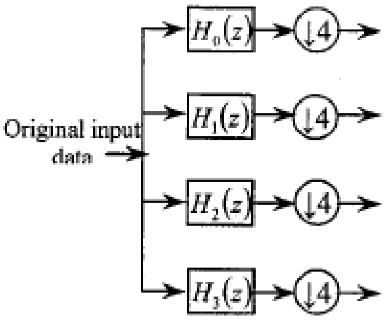


Fig.1: (b) Two-scale filterbank structure using the SLT.

In the compression scheme using SLT, the data is first applied to two-level filter structures H0(z), H1(z), H2(z), and H3(z). The output of these filters are down sampled by a factor of 4, which are the transform coefficients of the input data obtained after the convolution operation of the original data with the filter coefficients , as shown in figure 1. The transform coefficients are then thresholded using a suitable parameter. The inverse slantlet transform are performed on these thresholded coefficients to reconstruct the original data [8].

3.Experimental Results

The proposed image denoising method has been implemented using Matlab 7.0 on the various noisy images and report the results for the four 512x 512 standard test images Lena.png, Barbara.png, Parliament.bmp and Lena.jpg . The images are decomposed using Wavelet and Wavelet-like transforms to the five level and they are contaminated with Gaussian random noise with standard deviations 10, 20, 30, 40 and so on. A good estimator of threshold is the median of absolute deviation (MAD) using the highest level wavelet coefficients [3].

Table 1. Comparative study of Image Denoising method using DWT and SLT

Images	**MSE**		**PSNR**		**Selesnick**
	DWT	**SLT**	**DWT**	**SLT**	**main_dwt**
Lena.png	25.0058	29.1982	34.6513	33.4772	34.8633
Barbara.png	37.5278	43.1847	32.3865	31.7856	32.1841
Parliament.bmp	17.3933	19.7541	35.7270	35.1742	35.5457
Lena.jpg	16.6942	15.5065	37.8393	36.2257	37.7429

Table 2. Analysis of Proposed method for MRI image

Sigma, σ	MSE		PSNR		Selesnick
	DWT	SLT	DWT	SLT	main_dwt
10	9.9603	15.1108	38.1481	36.3379	37.7570
20	24.0616	40.3264	34.3176	32.0749	34.0104
30	41.2384	70.4881	30.3564	29.6496	31.7908
40	59.9019	105.0434	29.1155	27.9161	30.0792

In Table 1, we summarized the results of proposed algorithm for 512 x 512 images of different formats. It is observed that DWT based proposed method outperforms Selesnick Wavelet based Bivariate thresholding method and BlockShrink thresholding methidd using the wavelet-like transform (SLT) (reference figure 2).

In Table 2, we experimented the proposed method for the MRI image with noise density varying from 10 to 100, and have summarized the results for noise density 10, 20, 30, and 40, respectively. It is again found that DWT based proposed method outperforms the Selesnick Wavelet based Bivariate thresholding method and BlockShrink thresholding methidd using the wavelet-like transform (SLT) (reference figure 3).

In figure 4, the denoised images obtained for lena.png and mri.jpe from the proposed algorithms are shown.

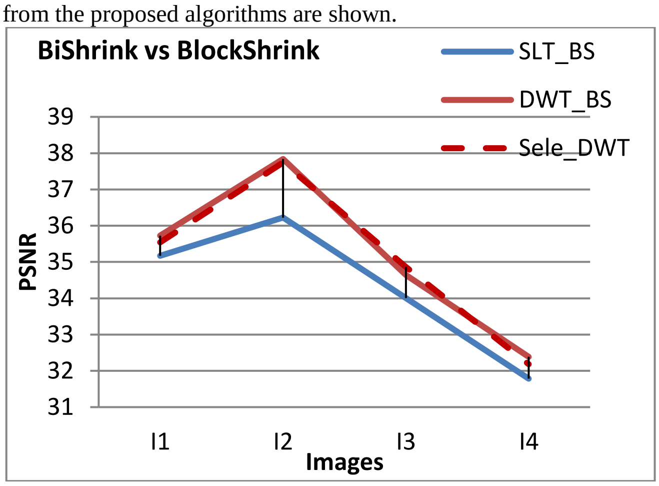


Fig.2 Performance of BlockShrink vs Bivariate basedr image denoising

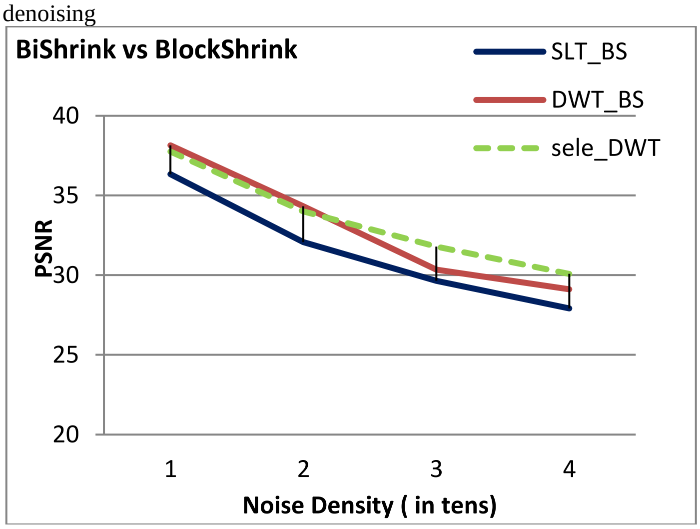
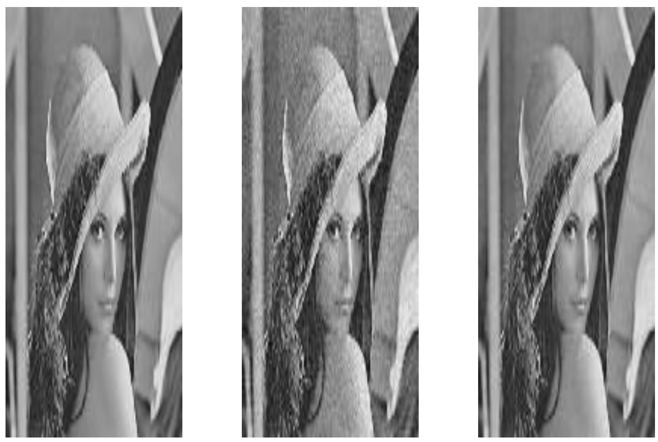
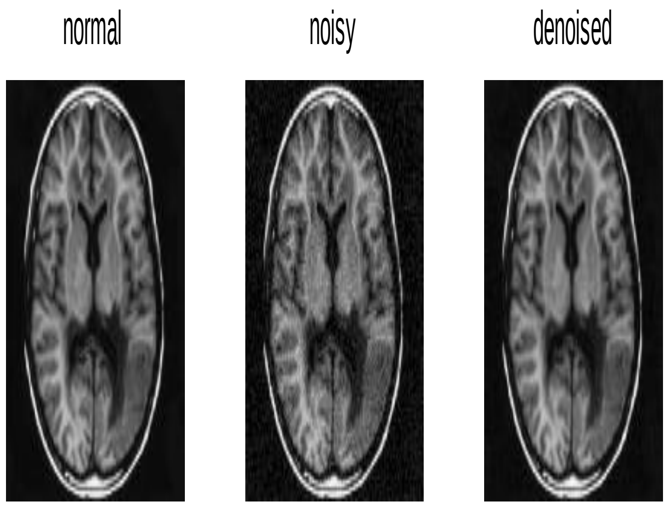


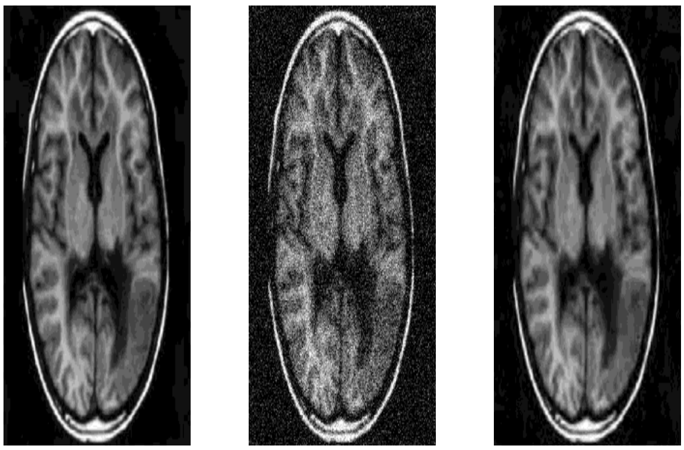
Fig.3 Noise density vs PSNR of proposed method using DWT and SLT and Selelsnick Wavelert based BiShrink method



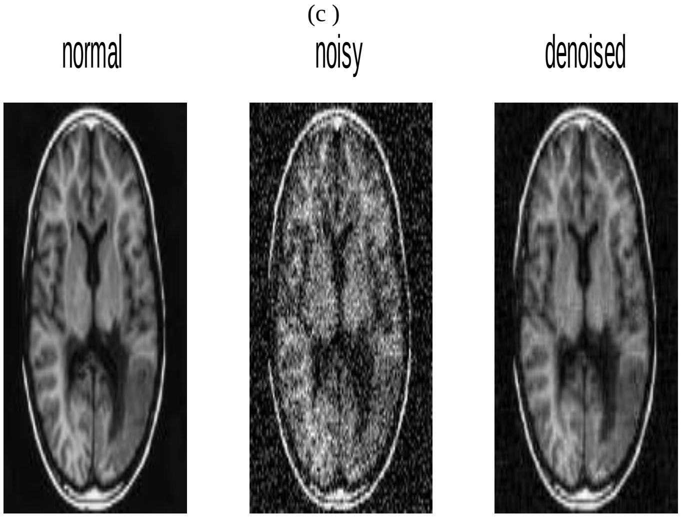
(a)



(b)



(c)



(d)

Fig. 4 Output of proposed algorithms using DWT for images (a) Lena.png; (b) mri.jpe (sigma=10); (c) mri.jpe (sigma=40); (d) SLT based mri.jpe (sigma=40).

4.Conclusions

This study gives the image denoising algorithm based on wavelet and wavelet-like transform thresholding method. BlockShrink is selected for the implementation purpose as it is found to be better than the other conventional wavelet thresholding methods. It is observed that DWT based BlockShrink thresholding methd outperforms the Wavelet based Bivariate Shrink thresholding, and also the SLT based BlockShrink thresholding method in terms of PSNR for the image denoising. The research work is also done by researchers/scientists for image denoising based on other transforms such as curvelets, contourlets and Dual Tree complex wavelet transform using the thresholding and filter techniques.

The important issue in developing such method is finding an optimal value for thresholding parameter so that it may not cause blur, artifacts and the resulting image may not lose any signal values. In future, we would like to work in this direction and will use other better transforms.

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References

[1] B Alpert, GR Coifman, V Rokhlin. Wavelet-like bases for the fast solution of second kind integral equations, SIAM J. Sci. Comput., 14, 1993, 159-184

[2] Z Dengwen S Xiaoliu. Image Denoising Using Block Thresholding, IEEE science society,Congress on Image and Signal Processing, 2008.

[3] DL Donoho, M Jhonstone. Wavelet shrinkage: Asymptopia? J.Roy.Stat.Soc., SerB, 57, 1995, 301-369.

[4] AFathi, AR Naghsh-Nilchi. Efficient Image Denoising Method Based on a New Adaptive Wavelet Packet Thresholding Function, IEEE Transaction On Image Processing, 21(9), 2012.

[5] Y Hawwar, A Reza. Spatially Adaptive Multiplicative Noise Image Denoising Technique, IEEE Transaction On Image Processing, December, 11(12), 2002.

[6] S Kother Mohideen, SArumuga Perumal, MMohamed Sathik. Image De-noising using Discrete Wavelet transform", International Journal of Computer Science and Network Security (IJCSNS), January 8(1), 2008.

[7] R Kumar, BS Saini. Improved Image Denoising Technique Using Neighboring Wavelet Coefficients of Optimal Wavelet with Adaptive Thresholding, International Journal of Computer Theory and Engineering, 4(3), 2012.

[8] Sushil Kumar, SK Muttoo. An Overview on Wavelet Transforms in Image Data Hiding", Proceeding of the National Conference on computing for Nation development, 2010, 263-268

[9] S Mupparaju1, B Naga Venkata Satya Durga Jahnavi. Comparison of Various Thresholding Techniques of Image Denoising, International Journal of Engineering Research & Technology (IJERT), 2(9), 2013

[10] VNaga Prudhvi Raja, T Venkateswarlu, Denoising of medical images using dual tree complex wavelet transform, Procedia Technology 4, 2012, 238 – 244

[11] H Naimi, ABH Adamou-Mitiche, L Mitiche, Medical image denoising using dual tree complex thresholding wavelet transform and Wiener filter, Journal of King Saud University – Computer and Information Sciences 27, 2015, 40–45

[12] S.S.Patil, A.B.Patil, S.C.Deshmukh, M.N.Chavan, "Wavelet Shrinkage Techniques for Images", International Journal of Computer Applications, 7(1), 2010, 0975 – 8887.

[13] Rajni, Anutam, Image Denoising Techniques-An Overview, International Journal of Computer Applications (0975 – 8887) 86(16), 2014

[14] Ivan W.Selesnick, The Slantlet Transform, IEEE transactions on signal processing, 47(5), 1998, 1304-1312.

[15] Vijayalakshmi. A, Titus.C and Lilly Beaulah.H, Image Denoising for different noise models by various filters: A Brief Survey, International Journal of Emerging Trends & Technology in Computer Science (IJETTCS), 3(6), 2014.