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Denoising of Natural Images using Modified VISUShrink on Shearlet Transform

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***Abstract*—Image denoising is a challenging task as some information contents like that of edges are generally lost in this process. Wavelet transform is used to denoise a 1-D signal, as it can represent point singularity very well. Thereby, it can retain the sudden changes in the signal, even after removing the noise. But an image is a 2-D signal and singularities in it can occur along a curve. Wavelet transform is not a good tool to handle this situation. Shearlet transform can be used instead of wavelet transform in image denoising. There are many thresholding algorithms for the wavelet transform. One such is VISUShrink, a universal thresholding algorithm. This paper proposes a universal thresholding algorithm for Shearlet transform and compares its performance with that of VISUShrink on symmlet4 and daubechies4 wavelets. The results show that the proposed algorithm performs better in most cases. A maximum of 24% increase in PSNR and 27% increase in SSIM are observed.**

***Index Terms*— VISUShrink, hard thresholding, soft thresholding, shearlet transform.**

I. INTRODUCTION

Image processing has been a hot area of research for decades. It has applications in computer vision, medical imaging, image denoising etc. Many a times, the obtained image is noisy. The noise gets added to the image while capturing the image or from the communication channel through which the image is guided from source to destination. These images, if directly used in algorithms like edge detection, object identification etc., may give poor results. So, it is very important to denoise the noisy image before using it as input to other algorithms for processing. The challenge in denoising is to retain the image information without any change and remove the noise completely. Both are contradictory in nature, i.e.; if it is attempted to remove the noise completely, then the information content in the image, in particular, the edge information, is affected. The edges become blurred in the process. This may have adverse effect on object detection. So, image denoising is still an active area of research.

Image denoising algorithms can be broadly divided into two categories; namely, spatial domain methods and transform domain methods. Mean filtering is a linear spatial domain method [1] which does low pass filtering. Generally, the image information content is of low frequency. But noise is present throughout the spectrum. If

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the noise is white, then it has a flat spectrum. Mean filtering removes the noise in the high frequency regions. At the same time, it also removes the high frequency information content in the image. As a result, the edges in the denoised image are blurred. Median filter is a non-linear spatial domain method. It retains the edges. But the problem with the method is that, it cannot distinguish whether a pixel is noisy or not. Wiener filter is another spatial domain filter [2]. It requires the image as well as the noise to be zero-mean. It uses linear MMSE estimation technique.

Wavelet transform is the most commonly used transform domain technique for univariate signal denoising. It represents the point singularity well. Therefore, it can retain the sudden changes in the signal, at the same time removing noise by thresholding the coefficients, except that of low frequency. But image is a multivariate signal, which may have singularities along a curve [3]. Wavelet transform is not a good tool to represent edges (except horizontal and vertical edges). Even then, it shows better denoising performance when compared with that of spatial domain methods. This is due to many thresholding algorithms used. VISUShrink is a universal non-adaptive threshold [4]. It uses same threshold for all the high frequency sub-bands in different levels of decomposition. SURE-Shrink [5] uses different thresholds for different sub-bands. BayesShrink is an adaptive threshold for minimizing the Bayes risk [6]. ProbShrink uses a probabilistic shrinkage method [7]. A comparison of denoising performance of above shrinkage algorithms is given in [8].

The coefficients corresponding to the edges have larger values for many scales in a wavelet transform. This means, in order to reconstruct edges, all these coefficients are needed. This creates a problem in image denoising. The curvelet transform [9], contourlet transform [10] and shearlet transform [11] are some of the transforms proposed to overcome this problem in wavelet transform. Curvelet transform lacks multiresolution analysis, whereas in contourlet transform, only discrete parameters are possible for the directional representation [12]. Shearlet transform can be used to overcome the drawbacks in these transforms.

The objective of this paper is to propose a universal threshold on shearlet transform, just like VISUShrink on wavelet transform, for image denoising and compare the denoising performance of the proposed threshold on shearlet transform with that of VISUShrink on wavelet transform, under different noise variances. The remaining portion of this paper is organized as follows: In section II, methodology is given in detail. In this section, the shearlet transform is introduced and the new algorithm is proposed. Results and discussions are given in section III. Section IV concludes the paper.

II. METHODOLOGY

A. Shearlet Transform

In a discrete wavelet system, data is represented in terms of basis of the signal space, which are scaled and shifted mother wavelet. This results in a non-redundant representation of data in a wavelet system. But a discrete shearlet constitutes a Parseval's frame, which results in a redundant representation of data. Wavelet transform is a separable transform, but shearlet transform is not.

A shearlet system consists of dilation and translation of a 2-D generating function ψ, called shearlet. The parabolic scaling matrix A_a and the shear matrix S_s are defined as:

$$A_a = \begin{bmatrix} a & 0 \\ 0 & \sqrt{a} \end{bmatrix} \text{ and } S_s = \begin{bmatrix} 1 & -s \\ 0 & 1 \end{bmatrix} \quad (1)$$

where $a > 0$ and $s \in R$. The associated shearlet system [12] is given by;

$$\left\{\psi_{jkm}(x) = 2^{-\frac{3}{2}j}\, \psi\left(S_{-k}A_{4^{-j}}\, x - m\right) : j,k \in Z, m \in Z^2\right\} \quad (2)$$

where *j* is the scale parameter, *k* gives the direction of singularity and *m* gives the position of singularity.

The shearlet transform of an image *f* is given by,

$$SH_\psi f(j, k, m) = \langle f, \psi_{jkm} \rangle \quad (3)$$

The equivalent tiling in frequency domain for 3 levels of decomposition is given in Fig. 1(a). It is referred to as shearlets on the cone. The corresponding tiling in frequency domain in wavelet transform is shown in Fig. 1(b). In Fig. 1(a), the lowest frequency components are towards the centre, whereas in Fig 1(b), they are towards the top-left corner.

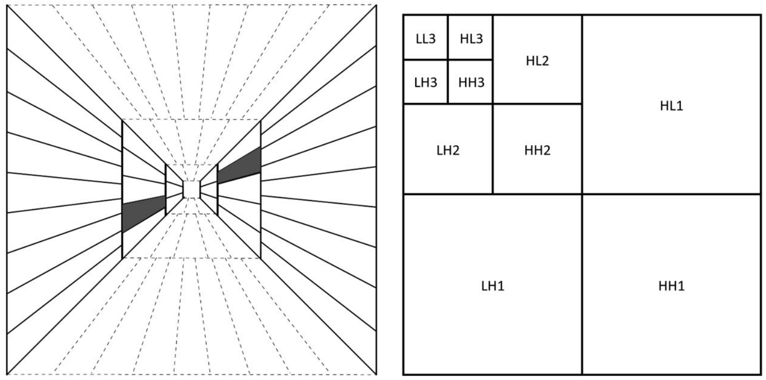


Figure 1. Tiling of frequency domain (a) shearlets on the cone [12] (b) wavelet transform for 3 levels of decomposition

B. Thresholding

Thresholding is of two types; hard thresholding and soft thresholding. In both these methods, if the absolute value of a coefficient is less than the threshold, it is made 0. There are no changes to other coefficients in the case of hard thresholding. In soft thresholding, the magnitudes of other coefficients are reduced by the threshold.

C. VISUShrink

The universal threshold for VISUShrink in the case of additive white Gaussian noise (AWGN) with standard deviation σ, is given in [4];

$$th_{visu} = \sigma\sqrt{2\log(N)} \tag{4}$$

where the image is of size NxN.
The value of σ is seldom known. So, its estimate $\hat{\sigma}$ is used instead [13].

$$\hat{\sigma} = \frac{median(|HH1|)}{0.6745} \tag{5}$$

where HH1 is the diagonal high frequency component of first level wavelet decomposition.
For denoising using shearlet transform, the universal threshold is given by;

$$th_{visu-shearlet} = \begin{cases} 0.4\, th_{visu} & ; hard\ thresholding\ and\ nL < 3 \\ 0.2\, th_{visu} & ; hard\ thresholding\ and\ nL \geq 3 \\ 0.1\, th_{visu} & ; soft\ thresholding\ and\ nL < 3 \\ 0.05\, th_{visu} & ; soft\ thresholding\ and\ nL \geq 3 \end{cases} \tag{6}$$

where nL is the total level of decomposition.

D. Experimental Set Up

Denoising performance of two wavelets; symmlet4 and daubechies4 are compared with that of shearlet transform. Five standard natural images of size 512x512 are used here; they are baboon, barbara, cameraman, lena and peppers. All these images were subjected to AWGN of standard deviations 5, 10, 15, 20, 25 and 30. For each standard deviation, the total levels of decomposition were varied from 1 to 4. Thresholding (both hard and soft) is done on all the sub-bands except the lowest frequency sub-band in wavelet transform and shearlet transform. The images were reconstructed using the lowest frequency sub-band and the thresholded sub-bands. The comparison is done based on Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM).

$$PSNR = 10\, log_{10}\left(\frac{255^2}{MSE}\right) \tag{7}$$

where the image is of size MxN and MSE is the mean-squared error between the original image and the reconstructed image. PSNR is measured in dB.

$$SSIM(X,R) = \frac{(2\mu_X\mu_R + C_1)(2\sigma_{XR} + C_2)}{(\mu_X^2 + \mu_R^2 + C_1)(\sigma_X^2 + \sigma_R^2 + C_2)} \tag{8}$$

where X, R, μ_X, μ_R, σ_X^2, σ_R^2 and σ_{XR} are the original image, reconstructed image, mean of X, mean of R, variances of X, variance of R and the covariance between X and R, respectively. C_1 and C_2 are pre-defined constants. The average PSNR values and SSIM values for each level of decomposition and each noise standard deviations are used for comparison. SSIM lies between -1 and 1. Higher the value, better is the algorithm.

III. Results & Discussions

The average PSNR values for hard thresholding and soft thresholding are tabulated in Tables I and II, respectively. For nL = 1, 2 and 3, the proposed algorithm performed better in all the cases. But for nL = 4, VISUShrink on symmlet4 performed better when the noise is higher. The average SSIM values for hard thresholding and soft thresholding are tabulated in Tables III and IV respectively. For nL = 2 and 4, SSIM of proposed algorithm is better in all the cases. But for nL = 1 and 3, at higher noise, SSIM values are slightly less than that for VISUShrink on wavelets. From the tables I to IV, it is clear that, shearlet transform with the proposed universal threshold is better than the wavelet transforms in denoising natural images in most of the cases under consideration. In the cases in which the wavelet transform outperformed the shearlet transform, the margin is very less. It shows that the shearlet transform is a better tool to denoise natural images when compared to wavelet transform. In case of both PSNR and SSIM, the difference decreases with the increase in noise. The denoising capacity of shearlet is evident from Fig. 2. A small portion of the image lena is enlarged to see the effect of these denoising methods clearly. The results corresponding to nL = 3 and $\sigma = 15$ are shown in Fig. 2(a) to (h). From the figure, it is evident that, denoising using the shearlet transform gives visually more appealing images than using wavelet transform.

TABLE I. PSNR (DB) - HARD THRESHOLDING

nL	σ	Symmlet4	Daubechies4	Shearlet
1	5	33.10	33.11	**35.77**
	10	29.24	29.25	**31.17**
	15	26.92	26.93	**28.39**
	20	25.20	25.20	**26.31**
	25	23.80	23.80	**24.65**
	30	22.61	22.62	**23.26**
2	5	32.32	32.32	**33.06**
	10	28.86	28.86	**29.53**
	15	26.87	26.88	**27.47**
	20	25.53	25.51	**26.15**
	25	24.51	24.51	**25.12**
	30	23.70	23.70	**24.34**
3	5	32.16	32.14	**35.19**
	10	28.59	28.60	**30.86**
	15	26.66	26.61	**28.41**
	20	25.35	25.33	**26.62**
	25	24.39	24.33	**25.26**
	30	23.63	23.56	**24.13**
4	5	32.11	32.06	**33.62**
	10	28.55	28.52	**29.42**
	15	26.58	26.54	**27.07**
	20	25.23	25.19	**25.40**
	25	**24.25**	24.20	24.18
	30	**23.49**	23.45	23.22

TABLE II. PSNR (DB) - SOFT THRESHOLDING

nL	σ	Symmlet4	Daubechies4	Shearlet
1	5	30.67	30.71	**36.02**
	10	27.9	27.93	**30.65**
	15	26.13	26.18	**27.4**
	20	24.76	24.78	**25.02**
	25	23.58	**23.61**	23.17
	30	22.54	**22.57**	21.63
2	5	29.21	29.19	**35.25**
	10	26.77	26.76	**31.26**
	15	25.4	25.42	**28.72**
	20	24.52	24.5	**26.86**
	25	23.84	23.84	**25.36**
	30	23.31	23.33	**24.08**
3	5	28.73	28.68	**35.59**
	10	26.15	26.14	**30.76**
	15	24.81	24.76	**27.84**
	20	23.93	23.91	**25.65**
	25	23.31	23.26	**23.98**
	30	**22.85**	22.78	22.54
4	5	28.53	28.48	**34.8**
	10	25.93	25.87	**30.39**
	15	24.51	24.44	**27.66**
	20	23.56	23.51	**25.66**
	25	22.89	22.83	**24.1**
	30	22.41	22.32	**22.78**

TABLE III. SSIM - HARD THRESHOLDING

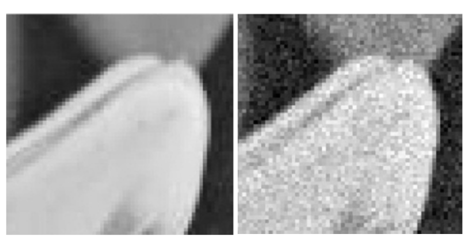
nL	σ	Symmlet4	Daubechies4	Shearlet
1	5	0.751	0.745	**0.782**
	10	0.609	0.608	**0.641**
	15	0.518	0.517	**0.550**
	20	0.450	0.450	**0.481**
	25	0.399	0.399	**0.428**
	30	0.356	0.357	**0.384**
2	5	0.706	0.707	**0.711**
	10	0.598	0.598	**0.608**
	15	0.522	0.523	**0.529**
	20	0.461	0.460	**0.471**
	25	0.414	0.414	**0.424**
	30	0.376	0.376	**0.389**
3	5	0.671	0.672	**0.717**
	10	0.565	0.567	**0.594**
	15	0.497	0.496	**0.513**
	20	0.443	0.444	**0.448**
	25	**0.398**	0.395	0.394
	30	**0.364**	0.363	0.351
4	5	0.664	0.667	**0.682**
	10	0.557	0.559	**0.562**
	15	0.483	**0.486**	0.479
	20	0.426	**0.428**	0.411
	25	**0.386**	0.383	0.358
	30	**0.347**	0.346	0.312

TABLE IV. SSIM - SOFT THRESHOLDING

nL	σ	Symmlet4	Daubechies4	Shearlet
1	5	0.727	0.723	**0.762**
	10	0.588	0.588	**0.610**
	15	0.501	0.500	**0.516**
	20	0.437	0.438	**0.446**
	25	0.389	0.390	**0.392**
	30	0.350	**0.350**	0.349
2	5	0.644	0.643	**0.765**
	10	0.539	0.538	**0.633**
	15	0.470	0.469	**0.545**
	20	0.417	0.416	**0.481**
	25	0.378	0.377	**0.430**
	30	0.348	0.348	**0.386**
3	5	0.579	0.581	**0.742**
	10	0.475	0.478	**0.596**
	15	0.412	0.414	**0.503**
	20	0.368	0.368	**0.435**
	25	0.333	0.332	**0.382**
	30	0.307	0.307	**0.338**
4	5	0.561	0.564	**0.739**
	10	0.452	0.454	**0.593**
	15	0.383	0.384	**0.499**
	20	0.335	0.334	**0.430**
	25	0.300	0.297	**0.376**
	30	0.275	0.270	**0.331**

IV. CONCLUSION

A universal thresholding algorithm for hard and soft-denoising of natural images using shearlet transform is proposed. Its performance is compared with that of VISUShrink on wavelet transform using symmlet4 and Daubechies4 wavelets. The metrics used for comparison are PSNR and SSIM. The results show that the proposed algorithm performs better in the case of both PSNR and SSIM. The performance improvement is more at low noise levels. It decreases as noise increases. There is a maximum increase of 24% in PSNR and 27% in SSIM. At higher noise levels, the proposed algorithm underperformed in some cases. VISUShrink is a universal thresholding algorithm. There are adaptive thresholding algorithms on wavelet transforms like SureShrink, BayesShrink, ProbShrink etc. Adaptive thresholding algorithm on shearlet transform can be implemented as a future work.



(a) (b)

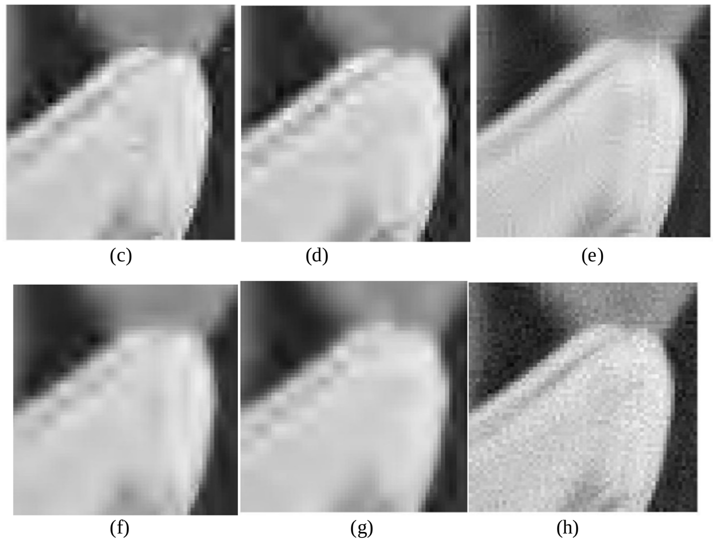


Figure 2 (a) Orignal Image, (b) Noisy Image, (c) – (e) image denoised using Symmlet4, Dubechies4 and Shearlet transform using hard thresholding , (f) – (h) image denoised using Symmlet4, Dubechies4 and Shearlet transform using soft thresholding

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