Analysis of Image Denoising Methods Using Various Wavelet Transform

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Abstract— **Image denoising is a method of removal of noise from original image. Spatial filtering methods and transform filtering methods are two classes of the image denoising. This survey mainly focused on various wavelet transform. A wavelet transform domain method gives a superior performance in image denoising applications. Wavelet transform mentioned here are DTWCT, OWT, RADL, and TIDFT, CT. These transform are used for representing edges and textures of an image. This makes it possible to separate noise from image signal distinctly in image denoising. Performances of various transform are compared by analyzing different parameters. In this paper a detailed survey has been carried out on various image denoising approaches and their performances on natural images were analyzed in case of visual quality.**

Index Terms— **Adaptive directional lifting, curvelet transform, Dual-tree, oriented wavelet, translation invariance.**

I.INTRODUCTION

The main task of considering the images is a noise reduction or suppression. In this task, we are focusing preservation of actual image features. Real world signals will get an departures from ideal signal. We call those departures as noise. A capture, acquisition and processing in an image is usually affected by noise. An important part of image processing systems is noise reduction. Generally, while preserving edges and contours the duty of a good image denoising model is to remove noise. The wavelet transform is a simple and elegant tool that can be used for many digital signal and image processing applications. Using a set of analyzing functions the wavelet transform provides multiresolution representations which are dilations and translations of a few functions (wavelets). It overcomes some of the limitations of the Fourier transform with its ability to represent a function simultaneously in the frequency and time domains using a single prototype function (or wavelet) and its scales and shifts [1]. The wavelet transform comes in several forms. The most compact representation is provided by critically sampled form of the wavelet transforms. Some of the most commonly used transforms for shrinkage-based noise reduction are the Wavelet Transform (WT) [2]–[4], the Steerable Pyramid Transform [5]–[7], the Contourlet Transform [8]–[10] and the Shearlet Transform [11]–[13]. Many kinds of denoising methods have been extensively discussed both in spatial and frequency domain. In essence, the key factor that lies in any successful denoising method is to find the different characteristics between signal and noise [14]-[17]. An image is often corrupted by noise in its acquisition or transmission. By retaining as much as possible the important signal features we can remove the noise.

II. DENOISING IMAGES USING VARIOUS WAVELET TRANSFORM.

A. Dual -tree Complex Wavelet Transform

The Discrete Wavelet Transform (DWT) is a founding stone for all applications of digital image processing from image denoising to pattern recognition, which passes through image encoding .While being a complete and invertible transform of 2D data, the Discrete Wavelet Transform which is also known as checker board pattern in which the data orientation analysis is impossible. Also we can say that, the DWT is not shift-invariant, which make it less useful for methods based on the computation of invariant features. In an attempt to solve these two problems affecting the DWT, Freeman and Adelson The concept of Steerable filters is first introduced [18], in which it can be used to decompose an image into a Steerable Pyramid, by using the Steerable Pyramid Transform (SPT) [5].The SPT is an over-complete representation of data, it also has the capability to correctly distinguish data orientations as well as it is being shift-invariant. But now the SPT is not devoid of problems for particularly, filter design can be messy, perfect reconstruction is not possible and computational efficiency can be a concern. Finally the energy response, has been represented with the help of Complex Wavelet Transform (CWT) [19].

TABLE I
PSNR RATIOS AND SSIM
SCORES FOR TEST IMAGES

		Noisy		Denoised	
Noise type	Image name	PSNR	SSIM	PSNR	SSIM
Gaussian	Lenna	27.43	0.58	35.78	0.95
	splash	27.68	0.49	36.37	0.93
	mandrill	27.45	0.73	34.38	0.98
Poissonian	Lenna	30.33	0.84	35.78	0.95
	splash	30.92	0.82	36.37	0.93
	mandrill	30.16	0.95	34.78	0.98
Speckle	Lenna	27.07	0.55	33.96	0.94
	splash	27.55	0.53	33.84	0.94
	mandrill	26.96	0.69	33.87	0.97

The above table I which shows PSNR ratios and SSIM scores

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for test images. Noise type mentioned here are Gaussian, poissonian, Speckle. And the given images are lenna, splash, and mandrill. The parameters PSNR & SSIM values are taken for both noisy and denoised images. Finally the various images are taken in both noisy and denoise form. And their values are compared with the help of parameters. Similarly to the SPT, we can retain the whole Fourier spectrum by using a factor of 4, i.e. there are 3 complex coefficients for each real one. The CWT is also efficient and it can be computed through separable filters but it still lacks in the Perfect Reconstruction property. At the cost of approximate shift-invariance Kingsbury also introduced the Dual-tree Complex Wavelet Transform (DTCWT), which has the added characteristic of Perfect Reconstruction. Though the topic is somewhat vast, we can only give a brief introduction of the 2D DTCWT. The reader is referred to the work by Selesnick for a comprehensive coverage on the DTCWT and the relationship it shares with other transforms.

B. Robust adaptive directional lifting

This section is concerned with the robust adaptive directional lifting (RADL) and its application in image denoising. To solve the problems stated above, we extend ADL to a new robust adaptive directional lifting (RADL)-based wavelet transform, which involves three additional parts. Image pixel classification based on noise variance estimation, which has the ability to classify all the pixels into two types: pixels belonging to texture regions and pixels belonging to smooth regions. Robust orientation estimation based on pixel classification and inter-scale correlation, which provides more accurate local orientation estimation than the previous method adopted in ADL. Optimal transform strategy performs the transform on pixel level instead of block level to avoid artifacts in the smooth regions. In this paper, the image discontinuities such as edges and textures are localized by pixel classification performed to the full-resolution image.

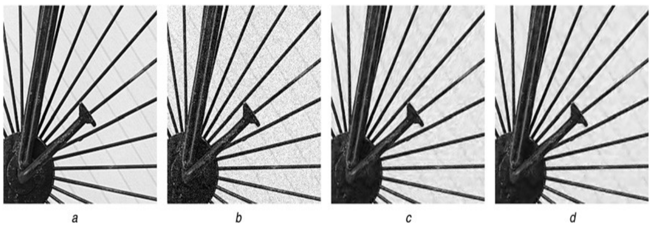

Fig. 1. Denoising results comparison
a Original image
b Noised image (s ¼ 20, PSNR ¼ 22.88 dB)
c Denoising by ADL transform strategy (PSNR ¼ 24.92 dB)
d Denoising by the proposed transform strategy (PSNR ¼ 25.05dB)

From the above Fig.1. Denoising results are compared with the help of parameter PSNR. In subdivision a.) It shows original image. b.) shows Noisy image .c.) shows how we are denosing an image with the help of transform strategy and d.) gives the denoising results of proposed transform. However, the lifting scheme is a pyramid transform, which means the size of each sub-band changes during the transform. However, a key issue named orientation estimation for ADL becomes inefficient and error prone in the noised circumstance. A robust adaptive directional lifting-based (RADL) wavelet transform for image denoising is proposed by authors and it is constructed ADL in an anti-noise way. Instead in this model, a simple model of pixel pattern classification is included into orientation estimation module to strong the robustness of this algorithm. And moreover, instead of determining the transform strategy based on sub-blocks, RADL is performed on pixel-level to correct better denoising results. Locations of the large magnitude coefficients that represent the image discontinuities change in different scales. Fortunately, it has been proved that there are strong correlation ships between the coefficients in different scales [20]. In critical situation sampled orthogonal wavelet decomposition, the position of large wavelet coefficients out of parents with lower resolutions can be detected with good accuracy [21]. It means that if the positions of image discontinuities in the high resolution are known, one can localize the large wavelet coefficients in low resolutions.

C.Translation invariant framelet transform

Consider a 2-D signal $x(\mathbf{n})$, $\mathbf{n} = [m, n]$ where m, n denote the index of row/column respectively.

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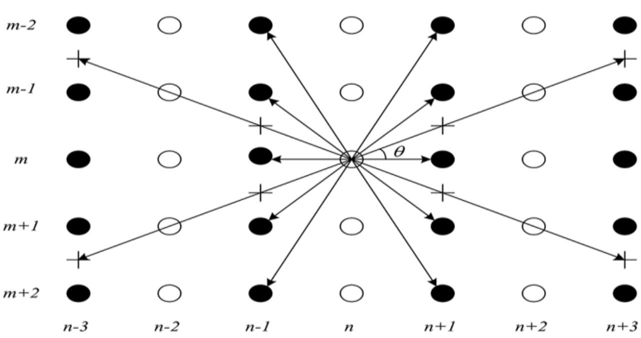

Fig.2.Directions used in the propose TIDFT, where the integral pixels '•'s and the fractional pixels '+'s are used for prediction'∘'s.

We assume that the 1-D transform is first applied in the horizontal direction and then in the vertical direction without a loss in generality. Assume that P(z) can be factorized into one couple of lifting steps, In this paper, seven directions as depicted in Fig.2 is preassigned to take part in the prediction step as well as in the update step .It is reasonable to expect that the transform will benefit from more directions used. Since the noise can deteriorate the estimation accuracy it is not feasible for a corrupted image. In extensions, the performance gain is limited with increasing directions. It will be further verified through experimental results. The lifting scheme is not translation invariant since the lifting procedure involves sub sampling. In many applications such as image denoising and pattern recognition, translation invariance is a desirable property. Translation invariance can be achieved through several ways. An over complete lifting scheme by using a smoothing Lazy wavelet in the split stage which does not subsample but smooth the input image. On the other hand, the most commonly used approach to achieve translation invariance is removing the down samplers and up samplers and up sampling the filter coefficients by a factor of 2l−1 in the l-level of the transform, so called algorithme à trous.

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TABLE II
COMPARISON OF PSNR (dB) FOR VARIOUS TEST IMAGES AND σ VALUES(BEST IN BRACKETS)

Image	σ	noisy	TIADL (SCE)	TIADL (ECE)
Lena (512*512)	10	28.13	36.14	(36.20)
	20	22.14	32.72	32.96
	30	18.66	31.09	31.24
	40	16.30	29.67	29.80
	50	14.54	28.43	(28.71)
Barbara (512*512)	10	28.13	33.64	33.81
	20	22.14	30.04	(30.37)
	30	18.66	27.86	(28.01)
	40	16.47	26.65	(26.54)
	50	14.76	25.00	(25.23)

The above table II which shows PSNR values for various test images as well as for σ values. The images mentioned here are Lena and Barabara.The image size taken here is 512*512.The value taken for σ values are 10, 20,30,40,50. And here the best values are taken in brackets. This tight frame is generated by a B-spline refinable function and two framelets with vanishing moments of order 2 and 1 respectively [22]. The constant signals cannot pass through the high-pass filter h2 but it can pass through h1, while linear signals can also pass through h1. Thus h1, h2 can be considered as singular detectors of order two and one respectively. For large numbers of natural images, these two framelets are capable of capturing the essential texture information since the natural images are often piecewise smooth and locally auto correlated. Thus this tight frame provides a sparse approximation to piecewise smooth images.

D. Curvelet transform

Curvelet transform, one of the multiscale geometric transforms, attempts to overcome the inherent limitations of traditional multistage representations such as wavelets. There contains various types of noises like the random noise, gaussian noise, salt, pepper and speckle noise. 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. Denoising using the Curvelet transform recovers the original image from the noisy one using lesser coefficients than denoising using the Wavelet transform.

TABLE III
PERFORMANCE MEASURE

Noise level σ	Curvelet denoised image PSNR(db)	Wavelet denoised image PSNR(db)
10	17.45	44.09
20	18.29	45.00

The above table III shows the Performance measure. The noise level σ are 10,20. Then the PSNR value for both curvelet denoised image and Wavelet denoised image. compare to the existing techniques the Wrapping based Curvelet transform [24] technique is conceptually simpler, faster and far less redundant. This technique is invertible with the rapid inversion algorithm of the same complexity. The curvelet transform [23] is same as the wavelet transform, it is also called as a multiscale transform, with frame elements is located by scale and parameters. It is different from the wavelet transform, it has directional parameters, and the curvelet pyramid consists of elements with a very high degree of directional specificity. In addition, the curvelet transform is based on a certain anisotropic scaling principle which is quite different from the isotropic scaling of wavelets. The elements follow a special scaling law, in which the length of the support of frame elements and the width of the support are linked by the relation: width ≈ length2. The curvelet transform provides the options to analyze an image with different block sizes, by using with a single transform.

E.Oriented wavelet transform.

Instead of using quincunx wavelets, according to an orientation map our approach consists in applying a 1D wavelet transform along directions selected adaptively for each wavelet coefficient. In this section, we can come to idea that the map is known and only there is a possibility of adaptation of the lifting steps is presented. It will present how to obtain the map depending on the application. To fully exploit the knowledge of the orientation, the high-frequency subbands are further decomposed in two subbands.The first contains contour [25] information and the other contains mostly residual noise.

TABLE IV
COMPARISON OF THE PSNR PERFORMANCE OF THE SEPARABLE WAVELET AND THE ORIENTED WAVELET

Image	lena	barbara	mandrill	Bike
Separable(db)	33.98	26.93	28.26	23.66
Oriented(db)	34.73	28.26	23.75	24.55

In table IV it shows the PSNR performance of separable wavelet and the oriented wavelet. The images taken here are lena, Barbara, mandrill, bike. Indeed, assuming the orientation is chosen to minimize the energy of each coefficient in the high-frequency subbands at each level, there still remain energetic coefficients corresponding to orientations not allowed in the map. Since the allowed orientations are not the same depending on whether the level is square or quincunx, orientation information on other levels may be used to further filter these coefficients along a proper orientation. For example, let us consider the first level of decomposition. The oriented lifting leads to a high-frequency band H0 which has been filtered along horizontal or vertical directions so as to minimize the coefficients energy.On the one hand; this subband does not contain any low-frequency information nor vertical or horizontal contours. On the other hand, diagonally oriented contours lead to coefficients of high magnitude in this subband. However, there requires a local diagonal or antidiagonal orientation to perform the decomposition in the subband H1 of the next level, this

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information may also be used to decorrelate the subband H0 by applying the above oriented lifting scheme again, but according to the diagonal/antidiagonal orientation map of the subband H1. This results in a H0H subband containing mostly noise and a H0L subband corresponding to diagonal contours, of half the size of H0. Therefore, the image energy is compacted even more. Thus, the orientation information is only important on edges, which concerns a small proportion of the pixels in natural images. It is therefore possible to propagate the orientation information from edges to other regions to reduce the entropy of the map substantially with a negligible impact on the overall distortion.

III. Results And Discussion

Various image denoising techniques using different transforms were analysed and dealt with the performance parameters of peak signal to noise ratio, signal to noise ratio, mean squared error in the process of noise removal for different natural images. It is proposed to obtain a better PSNR, SNR and MSE using the proposed algorithms. From the survey its clear that the noise removal using various transform shows better results.

IV. CONCLUSION

With the help of recent inventions and newly improved techniques, the Wavelet Transform plays a major role in image processing applications. In this paper, the wavelet based enhancement of gray scale images concept is highlighted .This article is also describes a survey of different noise removal techniques for denoising natural images. These methodologies were carried out on the various medical images to analyze their performance taking into measures such as peak signal to noise ratio, noise to signal ratio, mean squared error etc. From the literature analysis it is inferred that noise removal by different transform shows commendable results.

REFERENCES

[1] Shan Lal, Mahesh Chandra, Gopal Krishna Upadhyay, Deep Gupta, ―Removal of Additive Gaussian Noise by Complex Double Density Dual Tree Discrete Wavelet Transform*" MIT International Journal of Electronics and Communication Engineering,* Vol. 1, No. 1, pp. 8-16 Jan 2011.

[2] H. A. Chipman, E. D. Kolaczyk, and R. E. McCulloch, "Adaptive bayesian wavelet shrinkage," *J. Amer. Stat. Assoc.*, vol. 92, no. 440, pp. 1413–1421, 1997.

[3] A. Chambolle, R. De Vore, N.-Y. Lee, and B. Lucier, "Nonlinear wavelet image Processing: Variational problems, compression, and noise removal through wavelet shrinkage," *IEEE Trans. Image Process.*, vol. 7, no. 3, pp. 319–335, Mar. 1998.

[4] D. Cho, T. D. Bui, and G. Chen, "Image denoising based on wavelet shrinkage using neighbor and level dependency," *Int. J. Wavelets, Multiresolution Inf. Process.*, vol. 7, no. 3, pp. 299–311, May 2009.

[5] E. P. Simoncelli and W. T. Freeman, "The steerable pyramid: A flexible architecture for multi-scale derivative computation," in *Proc. 2nd Annu. Int. Conf. Image Process.*, Oct. 1995, pp. 444–447.

[6] F. Rooms, W. Philips, and P. Van Oostveldt, "Integrated approach for estimation and restoration of photon-limited images based on steerable pyramids," in *Proc. 4th EURASIP Conf. Focused Video/Image Process. Multimedia Commun.*, vol. 1. Jul. 2003, pp. 131–136.

[7] H. Rabbani, "Image denoising in steerable pyramid domain based on a local laplace prior," *Pattern Recognit.*, vol. 42, no. 9, pp. 2181–2193, Sep. 2009

[8] S. Foucher, G. Farage, and G. Benie, "Sar image filtering based on the stationary contourlet transform," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, Jul.–Aug. 2006, pp. 4021–4024.

[9] W. Ni, B. Guo, Y. Yan, and L. Yang, "Speckle suppression for sar images based on adaptive shrinkage in contourlet domain," in *Proc. 8th World Congr. Intell. Control Autom.*, vol. 2. 2006, pp. 10017–10019

[10] K. Li, J. Gao, and W. Wang, "Adaptive shrinkage for image denoising based on contourlet transform," in *Proc. 2nd Int. Symp. Intell. Inf. Technol. Appl.*, vol. 2. Dec. 2008, pp. 995–999.

[11] Q. Guo, S. Yu, X. Chen, C. Liu, and W. Wei, "Shearlet-based image denoising using bivariate shrinkage with intra-band and opposite orientation dependencies," in *Proc. Int. Joint Conf. Comput. Sci. Optim.*, vol. 1. Apr. 2009, pp. 863–866.

[12] X. Chen, C. Deng, and S. Wang, "Shearlet based adaptive shrinkage threshold for image denoising," in *Proc. Int. Conf. E-Bus. E-Government*, Nanchang, China, May 2010, pp. 1616–1619

[13] J. Zhao, L. Lu, and H. Sun, "Multi-threshold image denoising based on shearlet transform," *Appl. Mech. Mater.*, vols. 29–32, pp. 2251–2255, Aug. 2010.

[14] Donoho, D.L.: 'De-noising by soft-thresholding', IEEE Trans. Inf. Theory, 1995, 41, (3), pp. 613

[15] Deng, G., Tay, D.B., Marusic, S.: 'A signal denoising algorithm based on overcomplete wavelet representations and gaussian models', Signal Process., 2007, 87, (5), pp. 866–876

[16] Elad, M., Aharon, M.: 'Image denoising via sparse and redundant representations over learned dictionaries', IEEE Trans. Image Process., 2006, 15, (12), pp. 3736–37454

[17] Elad, M., Matalon, B.: 'Image denoising with shrinkage and redundant representations'. IEEE Computer Society Conf. on Computer Vision and Pattern Recognition, 2006, vol. 2, pp. 1924–1925

[18] W. Freeman and E. Adelson, "The design and use of steerable filters,"*IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 13, no. 9, pp. 891–906, Sep. 1991.

[19] N. G. Kingsbury, "Image Processing with complex wavelets," *Philos. Trans. Math. Phys. Eng. Sci.*, vol. 357, no. 1760, pp. 2543–2560,

[20] Chang, S.G., Yu, B., Vetterli, M.: 'Spatially adaptive wavelet thresholding with context modeling for image denoising',IEEE Trans. Image Process., 2000,9, (9),pp.1522–1531

[21] zurica, A.P., Philips, W.: 'Estimating the probability of the presence of a signal of interest in multiresolution single- and multiband image denoising', IEEE Trans. Image Process., 2006, 15, (3),pp.645–665

[22] Y. Tanaka, M. Hasegawa, S. Kato, M. Ikehara, and T. Q. Nguyen, "Adaptive directional wavelet transform based on directional prefiltering,"*IEEE Trans. Image Process.*, vol. 19, no. 4, pp. 934–945, Apr2010.

[23] Shanshan Wang, Yong Xia, Qiegen Liu, Jianhua Luo, Yuemin Zhu, David Dagan Fang, "Gabor feature based non-local means filter for texture image denoising.

[24] R.Sivakumar, "Denoising of Computer Tomography

ISSN: 2278 – 909X

Images using curevelet transform", ARPN Journal of Engineering and Applied Sciences",February2007
[25] M. N. Do and M. Vetterli, "The contourlet transform: An efficient directional multiresolution image representation," *IEEE Trans. Image Proc.*, Oct. 2003.

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