Research Article

Efficient Image Representation Based on Ripplet Transform and PURE-LET

Ayush dogra[1*], Sunil agrawal[2], Niranjan khandelwal[3]
[1*]Department of Electronics and Communication, Panjab University (uiet), India.
[2]Department of Electronics and Communication, Panjab University (uiet), India.
[3]Department of Radio-diagnosis, PGI Chandigarh, India.
***Corresponding author's E-mail:** ayush123456789@gmail.com

Accepted on: 20-08-2015; **Finalized on:** 30-09-2015.

ABSTRACT

To execute the different image processing tasks like- image fusion, image registration & image compression etc there should be efficient representation of image data with less computations, less complexity & less storage memory. In this paper, we propose a novel image representation method based on PURE-LET in the unnormalized Haar wavelet domain & Ripplet transform type-1. The performance of proposed method is evaluated by psnr & mse.

Keywords: image fusion, Ripplet transform, Haar wavelet, PURE-LET, psnr.

INTRODUCTION

Image representation is important task for image processing tasks like image fusion[1], image registration[2-3], image mosaicing, image enhancement[4-5] & pattern recognization. To execute various image processing tasks there should be efficient representation of an image with reduced singularities. Primitive transforms like Fourier transforms & wavelet are quite good to represent one dimensional signal but represent 2D signal with discontinuities like edges & contours. Discontinuities like edges & contours are main concern to address in an image in the coming time. Fourier transform & wavelet transform are quite capable to resolve the singularities in 1D but cannot resolve in 2D signal (image). To overcome these discontinuities many other image transforms such as Ridgelet[6], Curvelet[7] & Contourlet[8] have been reported in the last decade. But these transforms resolves discontinuities to some extent. Ridgelet resolve singularities along lines, whereas Curvelet & Contourlet are only confined to resolve singularities along curves. Generalization of scaling law in Curvelet lead to formation of Ripplet. Curvelet is special case of Ripplet. Ripplet can represent the images by resolving the singularities along curves. This transform is quite capable to represent the shape of object.

As far as textures are concerned Ripplet is weak to represent textures. So to represent the whole image it is crucial to combine Ripplet with other transform such as DCT which is capable to represent textures. PURE-LET is technique devised for image restoration in the presence of shot noise.

This is similar to SURE approach[9] and SURE-LET[10]. In this paper, we conduct experiment on structural images such as MRI. To evaluate performance, both Ripplet transform & PURE-LET in the Haar wavelet domain are implemented on structural imaging modality. PURE-LET is directly implied on the images without adding Poisson noise. It is combined with median filter to enhance the results.

Ripplet Transform

This transform is proposed by Dr. Dapeng Oliver Wu with collaboration with Jun Xu . The mathematical representation of Ripplet transform type - 1 is derived in[11-14]. This transform has following properties (1) multi resolution (2) good localization (3) high directionality (4) scaling with arbitrary degree & support (5) anisotropy (6) fast coefficient decay. Ripplet is generalization of curvelet transform and devised to address the problem like edges and contours. Ripplet transform can represent an image into different scales & different directions due to anisotropic property. After implying discrete Ripplet transform, the source images are decomposed into low frequency sub bands & high frequency sub bands.

Pure-Let & Median Filter

PURE (poisson unbiased risk estimate) –LET (linear expansion of thresholds) is denoising functions for shot noise. PURE-LET[15-16] is designed for image restoration in the presence of shot noise. PURE-LET is denoising functions like PURE-shrink. PURE-LET is devised to do two functions-(1) signal preservation (2) noise –suppression in the presence of shot noise. PURE denoising function is used with unnormalized Haar wavelet transform. The advantages of PURE-LET are (1) less computations (2) less memory (3) less complexity. Unnormalized Haar discrete wavelet transform can be studied as two channel filter bank (low pass/high pass), with scaling coefficients at scales J =1 to 6. Due to orthogonal property of unnormalized Haar wavelet, it is easy to split mse into sub band and concurrently minimize the mse for every sub band. In the PURE-LET case the scaling coefficients and wavelet coefficients are dependent and even correlated too. The basic thresholding function & interscale sign dependencies can studied in[15]. Haar wavelet functions are isotropic and have less directional capabilities. To overcome this limitation, PURE is extended to Haar direction let domain which is anisotropic in every scales. The three PURE-LET variants are PURE-LET0, PURE-LET1, & PURE-LET2. Median filter[17] is non linear filter used for noise reduction. It preserves edges while removing noise from images. It is a kind of smoothing method.

Objective Evaluation Metrics for Image Quality

PSNR[18-19] is peak signal to noise ratio. It is computed in decibels. It is used as quality metric between original and reconstructed image. Higher the PSNR, higher is the quality of reconstructed image. MSE[18] is also an image quality metric. MSE is cumulative squared error between the reconstructed image & original image. Lower the value of MSE, lower will be error. The formulas for computing MSE & PSNR are follows[18]-

$$MSE = \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N}$$

M and *N* are the number of rows and columns in the input images, respectively. Then computes the PSNR using the following equation:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right)$$

Methodology

Digital images acquired by different sensors will be reconstructed by Ripplet transform type 1 & PURE-LET. The algorithms used are as follows-

Algorithm 1-

(1) Pre- process the test images.

(2) Apply PURE-LET 0,1,2 to test images & reconstruct the images.

(3) Apply median filter on the reconstructed images.

(4) Compute PSNR.

Algorithm 2-

(1) Pre- process the test images.

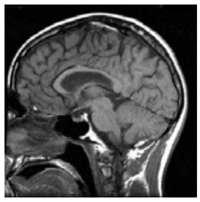
(2) Apply Ripplet type -1 transform to test images & reconstruct the images.

(3) Compute PSNR.

(4) Compute MSE.

RESULTS AND DISCUSSION

Source image is taken from Yiu Liu homepage[20], then imply Ripplet transform type-1 on this image at different coefficients 10000, 20000, 30000, 40000, 50000. The original source image is depicted in figure 1 and reconstructed images by Ripplet are depicted in figure 2. Similar approach is adapted for PURE-LET 0, 1 & 2. PURE-LET 0, 1 & 2 are implemented on the source image. No. of wavelet scales are varied from J=1 to 5 for PURE-LET 0, 1 & 2 separately. The no. of cycle shifts is set at 15 cyclic shifts. Median filter is applied on the reconstructed images by PURE-LET to enhance the quality, noise removal & edge preserving. The reconstructed images by PURE-LET 0, 1, & 2 are shown in figure 3, 4, 5 while the median filter results on these reconstructed images are shown on figure 6, 7 & 8. The PSNR, MSE calculations are shown in table 1, table2 & table3. The computation time for every computation is less than 10 seconds at 15 cyclic shifts.



(a)

Figure 1: original images[20]

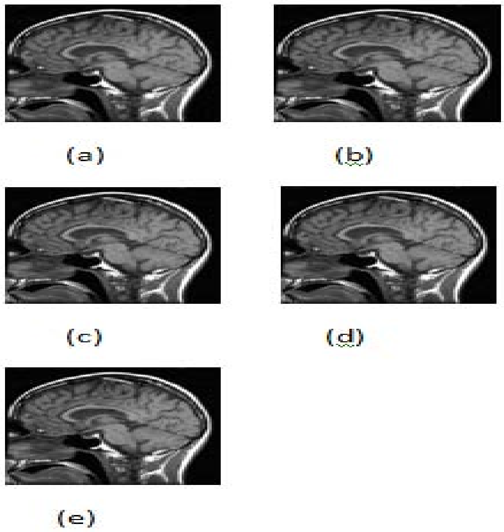


Figure 2: Reconstructed images at a)10000, b)20000, c)30000, d)40000, e)50000 Ripplet coefficients

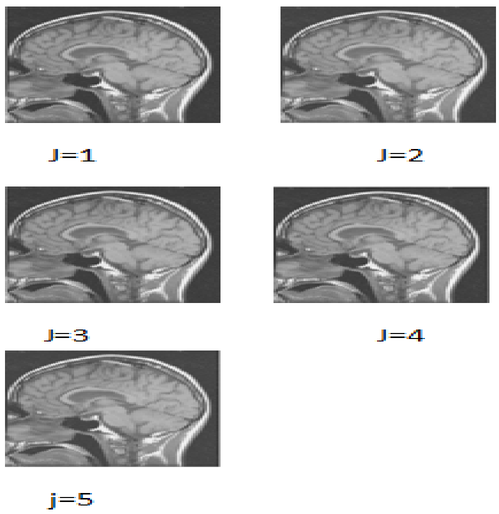


Figure 3: PURE-LET 0

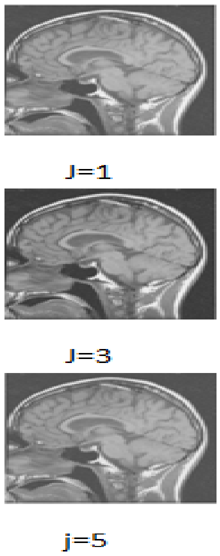


Figure 4: PURE-LET 1

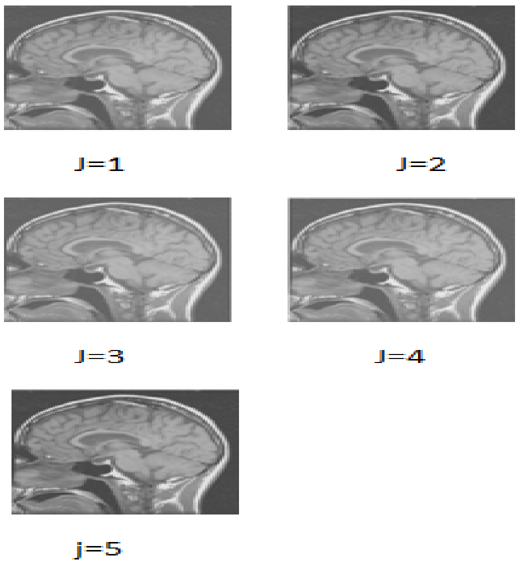


Figure 5: PURE-LET 2

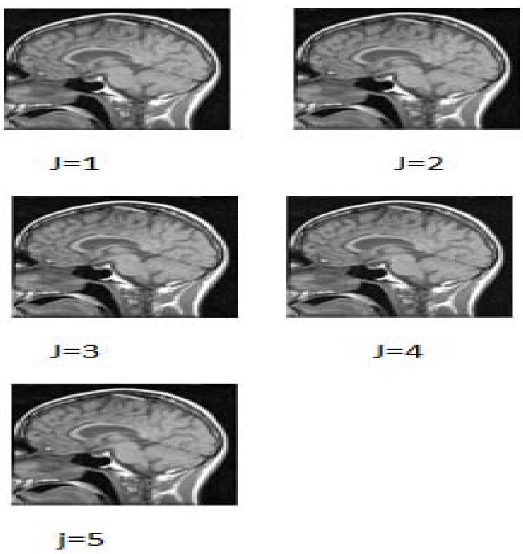


Figure 6: Median filter results on PURE-LET 0 reconstructed images at different scales

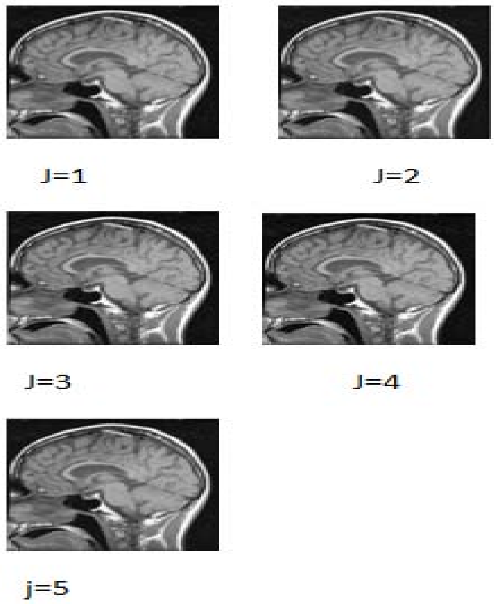


Figure 7: Median filter results on PURE-LET 1 reconstructed images at different scales

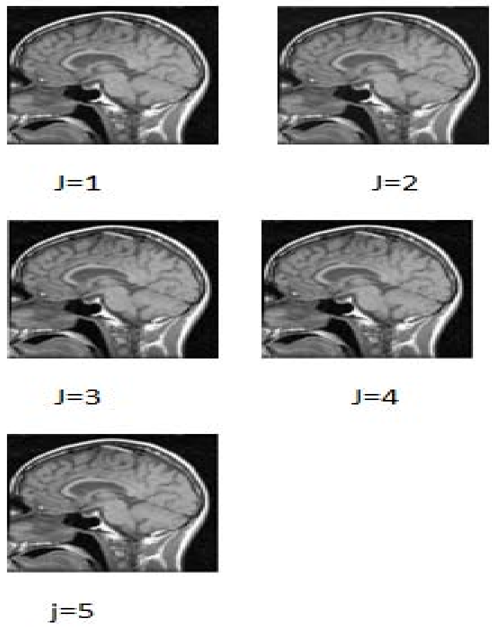


Figure 8: Median filter results on PURE-LET 2 reconstructed images at different scales

Table 1: PSNR between original images & Ripplet reconstructed images

Between original image (a) & reconstructed images at-different coefficients	PSNR
10000	29.3602
20000	31.0594
30000	31.7669
40000	32.0995
50000	32.2796

Table 2: MSE between original images & Ripplet reconstructed images

Between original image (a) & reconstructed images at-different coefficients	MSE
10000	75.3459
20000	50.9499
30000	43.2900
40000	40.0985
50000	38.4702

The significance of better & efficient image representation with enhanced quality is to execute different image processing tasks.

We have used three different approaches (1) Ripplet (2) PURE-LET (3) PURE-LET combined approaches. Ripplet transform showed improved results as compared to original images. PURE-LET 2 showed improved quality as compared to PURE-LET 0, 1. PURE-LET combined approaches showed better results than the PURE-LET 0, 1, 2. In PURE-LET approaches increase in cyclic shift increase computations time.

Table 3: PSNR for PURE-LET 0, 1, 2 & other algorithms

Different wave-let scales	Between image(a) & reconstructed images by PURE-LET 0	Between image(a) & reconstructed images by PURE-LET 1	Between image(a) & reconstructed images by PURE-LET 2	Between (a) & median filter reconstructed images implemented on PURE-LET 0 images	Between (a) & median filter reconstructed images implemented on PURE-LET 1 images	Between (a) & median filter reconstructed images implemented on PURE-LET 2 images
J=1	14.1454	14.3988	10.8287	19.6400	14.0621	20.4829
J=2	15.2157	15.3653	11.4306	21.0673	20.9353	18.4687
J=3	14.4006	14.3238	13.7121	19.9992	20.4964	20.7956
J=4	15.3243	12.2306	12.3439	18.0256	21.2991	23.9642
J=5	13.3243	12.5679	14.2815	19.8465	16.0048	20.2816

CONCLUSION

On the basis of PSNR & MSE calculated between original and reconstructed images at different Ripplet coefficients, it is depicted that reconstructed images by Ripplet transform showed improved quality as PSNR is increasing and MSE decreasing. The quality of image is further improved when increasing Ripplet coefficients from 10000 to 50000. Image quality is increased after processing by Ripplet type-1 transform. Ripplet transform provide efficient representation of images with singularities along smooth curves. Ripplet is capable of representing shape of an object, but they are not good representing textures. PSNR calculated for reconstructed images for PURE-LET 0, 1 & 2 reveals that reconstructed images at wavelet scale J=2 shows improve quality. At wavelet scale J=3, 4, 5 the image quality decreases. PURE-LET 2 shows better quality than PURE-LET 0 & 1. The image quality is enhanced when PURE approach is combined with median filter. As of now, PURE approach is used an efficient denoising function for shot noise. We tried to implement this function directly on noiseless images. Though the diagnostic quality of structural image modality is reduced after directly implying PURE-LET, but it shows better results when combined with median filter. Ripplet transform shows better result than PURE approach combined with median filter.

Future Scope

As Ripplet transform do not represent texture well. So there is necessity to combine Ripplet transform with other image transforms which give better texture representation. As a result the whole image can be represented well. Ripplet transform can be used instead to newly proposed Directionlet transform as it contains both anisotropy as well as high directionality property. PURE approach can be combined with other transforms & filters to gain better image representation. Though this approach can be good alternative for improving quality of images for functional medical modalities like PET, SPECT. In future we will extend PURE approach to yield better results.

This is first time when a denoising function exclusively designed for noise removal is directly applied onto the medical modality with no noise.

REFERENCES

1. Shen, Rui, Irene Cheng, and Anirban Basu. "Cross-scale coefficient selection for volumetric medical image fusion." Biomedical Engineering, IEEE Transactions on 60.4 (2013), 1069-1079.
2. Dogra, A., and M. S. Patterh. "CT and MRI Brain Images Registration for Clinical Applications." *J Cancer Sci Ther,* 6, 2014, 018-026.
3. DOGRA, AYUSH, and PARVINDER BHALLA. "CT and MRI Brain Images Matching Using Ridgeness Correlation."
4. DOGRA, AYUSH, and PARVINDER BHALLA. "Image Sharpening By Gaussian And Butterworth High Pass Filter."
5. Dogra, Anush, and Ayush Dogra. "Performance Comparison of Gaussian and Elliptic High Pass Filter." International journal of Advanced Biological and Biomedical Research 3.1 (2015), 93-96.

6. Do, Minh N., and Martin Vetterli. "The finite ridgelet transform for image representation." Image Processing, IEEE Transactions on 12.1 (2003), 16-28.
7. Starck, Jean-Luc, Emmanuel J. Candès, and David L. Donoho. "The curvelet transform for image denoising." Image Processing, IEEE Transactions on 11.6 (2002), 670-684.
8. Do, Minh N., and Martin Vetterli. "The contourlet transform: an efficient directional multiresolution image representation." Image Processing, IEEE Transactions on 14.12 (2005), 2091-2106.
9. Luisier, Florian, Thierry Blu, and Michael Unser. "A new SURE approach to image denoising: Interscale orthonormal wavelet thresholding." Image Processing, IEEE Transactions on 16.3 (2007), 593-606.
10. Blu, Thierry, and Florian Luisier. "The SURE-LET approach to image denoising." Image Processing, IEEE Transactions on 16.11 (2007), 2778-2786.
11. Xu, Jun, Lei Yang, and Dapeng Wu. "Ripplet: A new transform for image processing." Journal of Visual Communication and Image Representation 21.7 (2010), 627-639.
12. Das, Sudeb, Manish Chowdhury, and Malay Kumar Kundu. "Medical image fusion based on ripplet transform type-I." Progress In Electromagnetics Research B 30 (2011), 355-370.
13. Das, Sudeb, Manish Chowdhury, and Malay Kumar Kundu. "Brain MR image classification using multiscale geometric analysis of ripplet." Progress In Electromagnetics Research 137 (2013), 1-17.
14. Xu, Jun, and Dapeng Wu. "Ripplet transform for feature extraction." SPIE Defense and Security Symposium. International Society for Optics and Photonics, 2008.
15. Luisier, Florian. "Fast interscale wavelet denoising of Poisson-corrupted images." Signal Processing 90.2 (2010), 415-427.
16. Palakkal, Sandeep, and K. M. M. Prabhu. "Directionlet-based PURE-LET for Poisson Image Denoising." Proceedings of the International Conference on Image Processing, Computer Vision, and Pattern Recognition (IPCV). The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), 2012.
17. https://en.wikipedia.org/wiki/Median_filter
18. mathwork, accelerating the pace of engineering and science http://www.mathworks.in/help/vision/ref/psnr.html
19. Hore, Alain, and Djemel Ziou. "Image quality metrics: PSNR vs. SSIM."Pattern Recognition (ICPR), 2010 20th International Conference on. IEEE, 2010.
20. http://home.ustc.edu.cn/~liuyu1/dataset/source%20images.rar

Source of Support: Nil, **Conflict of Interest:** None.