ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

Sliced Ridgelet Transform for Image Denoising

V Krishnanaik[1], Dr.G.Manoj Someswar[2]

Ph. D. Research Scholar, Department of ECE, Mewar University, Chittorgarh, Rajashtan, India[1]

Professor, Department of ECE, Mewar University, CET, Chittorgarh, Rajashtan, India[2]

ABSTRACT: Image Quality becomes an essential aspect for various image and video processing based applications. Quality of captured images are often does not meet the expected quality scale due to noisy in images. Image noisy ratio effects on image processing and image relevant decision making applications, and cause to inaccurate and erroneous results. Image Noisy removing (Image De-noising) is the first and foremost requirement for any image and video processing applications. Although some previous researches were introduced various new approaches on this area, still this area is suffering from accuracy, quality and reliability. Henceforth, this thesis concentrates on implementing an accurate and scalable image de-noising approach to achieve the high quality, which helps better than existed technologies of image or video processing.

In order to overcome the above mentioned problems we are designing and implementing an integrated, comprehensive and scalable solution is sliced ridgelet transformation for image de-noising.This Research work introduces sliced ridgelet transform for image de-noising, and to achieve the scalability and accuracy and in a reliable manner of image processing. Image de-noising that is based on ridgelets computed in a localized manner and that is computationally less intensive than curvelets, but similar donoising performance. Sliced ridgelet transform’s ridge function is segregated to multiple slices with constant length. Single-dimension wavelet transforms are used to compute the angle values of each slice in sliced ridgelet transform. Ridgelet co-efficient are obtained for the base threshold calculation to implement the accurate de-noising.

This new method for image de-noising technique is based on two operations: one is the redundant directional wavelet transform based on the radon transform, and threshold designing of the ridgelet coefficient. This research work compares the accuracy and scalability of image de-noising with other popular approaches like wavelets, curvlets and some other inter-relevant technologies. Experimental results are proving that the sliced ridgelet approach is having the better performance than the other popular techniques.

KEYWORDS: Ridgelet Transform, Image Denoising, Curvlets, Ridgelet coefficient, Ridge function.

I. INTRODUCTION

In this era of internet, usage of image is increased day by day in different areas such as fashion, art, design, animation, advertising and finger print identification. Image processing is very important and base technology for many real time applications like image search engines, image clustering, image segmentation, Entropy detection etc. Image clarity (clear pixel resolution) is an important property of image and maximum percentage is expected for image processing applications. This is one of the factors to determine the accuracy of image processing results. The increased level of clarity will increase the result accuracy dramatically and also makes the results reliable.
Image blurriness is the common problem in the area of image processing, which is also called as noisy of image. This problem should be resolved before image processing to alleviate the burden and bottlenecks of image processing. Comparison, segmentation and clustering of an image are expecting the clear removal of noisiness in the given image is called as Image De-noising.

The recent proposed procedures by various authors has been introduced image de-noising based on transforms such as wavelets, curvelets, exploit redundancy and threshold to remove the noise without blurring the edges. In this research,

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

we introduced "Sliced Ridgelet Transform for Image De-noising" to mitigate the burden of image de-noising process and to improvise the image display resolution depth (image clarity) to extract the best results while working with image processing applications. This scheme also addresses the main issues and disadvantages of wavelet transform like Shift sensitivity, Poor Directionality and Absence of Phase information while doing the image de-noising process. The important characteristic of the de-noising technique introduced in this project is that it can reduce considerably the noise without destroying the edges of the objects in the image.Experimental results with MATLAB software is proving our thesis scalability, accuracy and reliability while comparing with other schemas like wavelet transform and curvelet transform. These results were stated that, usage of sliced ridgelet transform model is having the better performance than other transform schemas.

II. RELATED WORK

2.1 SLICED RIDGELET TRANSFORM

In this section we discuss about our proposed sliced ridgelet technology along with the thesis contributions. Initially we describe about the slice ridgelet technology and its terminology. After this, we explore our proposed objectives of this research in a sequential and interlinked manner. Most popular technologies of image de-noising are wavelet transform, curvelet transform and ridigelet transform. Ridigelet transform [4 and 5] was introduced to avoid the potential bottleneck problems of image processing are inevitability and non-redundancy. These problems were effecting on performance of image processing dramatically and caused to unexpected results and result invariants.

Recently ridgelet transform become an alternative to overcome the problems in image processing with wavelets transform. The 2D wavelet transform of images produces large wavelet coefficients at every scale of the decomposition. With so many large coefficients, the de-noising of noisy images faces a lot of difficulties. This is become a big problem in processing of images with an efficient legacy wavelet mechanism. Ridgelet transform was successfully applied on digital image processing with different orientations and locations. Unlike wavelet transforms [6 and 7], the ridgelet transform processes data by first computing integrals over different orientations and locations. A ridgelet is constant along the lines x1 cos β + x2 sin β = constant. In the direction orthogonal to these ridges it is a wavelet. Ridgelets have been successfully applied in image de-noising recently. Ridgelets is a novel feature in image processing, which applied in the research area of image de-noising. For each a>0, each b ∈R and each Θ∈[0,2π), the bipartite ridgelet ($_{\pi}$ a,b),: $R^2 \rightarrow R$is defined as

$$\lambda(a,b,{}_{\Theta}) = a^{(-1/2)}\, \lambda((x1 \cos \Theta + x2 \sin \Theta\ - b)/a),$$

whereλ is a predefined wavelet method. Ridgelet value is static with the lines

$$\lambda\ (x1 \cos x) + \lambda\ (x2 \sin y) = \text{static constant.}$$

Diagonal to these ridgesit is a well formed wavelet. Given an in variant bipartite image f(x1,x2), and we can write its ridgelet (for each (p>0) and (q ∈ R)) significant formula as:

$$R(p,q,\Theta) = p,q,\Theta,f[(\lambda)\ (x1,x2)\ d(x1)\ d(x2)].$$

The given below figure 1 shows the basic ridgelet function with its sliced transforms.

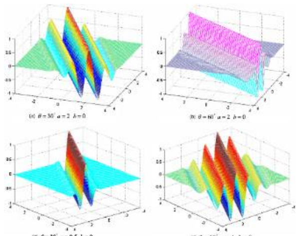


Fig 1 Basic Sliced ridgelets formation with various angular variable Θ values

The above diagram specifies the various constant Θ values and their respective ridgelets curved area of an image. By varying the values of a and Θ we just shown the image representations. As per the requirement these ridgelets might be scaled , shifted and rotated also.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

Sliced ridgelet transform is a multi-dimensional and precise wavelet transform with slices. In this approach the Θ is a random static constant and the a value will be change frequently. Ridgelets are quite varied from wavelets in the view of ridgelets parade very high directional sensitivity and are highly anisotropic. This high anisotropic value is caused to get the best results while implementing the image de-noising techniques. An exceeded ridgelet transform can be performed in the Fourier domain. Initially for the given image the2D FFT [8 and 9] is computed. Interpolation process will continue with along a number of straight lines equal to the selected number of projections. Each line passes through the center of the 2D frequency space, with a slope equal to the projection angle, and the number of interpolation points equal to the number of rays per projection. After the 1D inverse FFT along each interpolated ray, we perform a 1D wavelet transform.For Example, for an image with N bit per pixel, and slicing the image with a distinct constant pixel value will effects the results of image processing is called data compression. If we consider there is an image with 8-bits per pixel can represented to bit plans as shown below. In this case zero is the least significant bit (LSB) and 7 is the most significant bit (MSB). Here in the given below figure 3 we can observe some examples of sliced images at various bit planes.

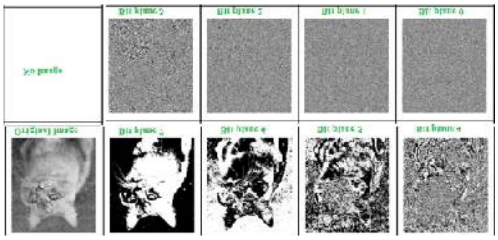


Fig 3. An 8-bit image and different bit-planes after slicing,

Original Image	(Bit Plane 8 + Bit Plane 7) Mask	Compressed Image	Original File Size	Mask File Size	Compressed File Size
			895K	25K	875K

Fig4 An8-bit image compression with mask 7-bit plane

The above image 3 represents the pgm image with 8 different bit planes, which starts from 0 and continues upto 7 (total 8 images). In the next figure 4 shows that a compressed image with 7 bit plane mask and the size comparison also can be seen. From that comparison we understood that, the compressed image size is less than the original image, even after compressing with the 7 bit plane mask.

Advantages of Image Slicing:

- Highlighting the contribution made by a specific bit and For pgm images, each pixel is represented by 8 bits.
- Each bit-plane is a binary image and Less the size even after compression with bit plane
- Processing done at each bit (pixel) level and Result Accuracy, scalability and Reliability

2.2 RADON TRANSFORM

As specified above our sliced ridgelet transform is using the Radon transform technique for 1-D and 2-D for fourier and wavelet transformation sake. Various image layers and their packed pixel content will be calculated by the approximate Radon transform formula is:

Coefficients can be calculated as:

$$w_{j+1}(\vartheta,\varphi) = c_j(\vartheta,\varphi) - c_{j+1}(\vartheta,\varphi)$$

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

Hence the Radon transform function is:

$$\hat{\psi}_{\frac{l_c}{2^j}}(l,m) = \hat{\phi}_{\frac{l_c}{2^{j-1}}}(l,m) - \hat{\phi}_{\frac{l_c}{2^j}}(l,m)$$

In the recursive manner:

$$\hat{w}_{j+1} = \hat{h}_j \widehat{G}_j$$

$$\text{where} \quad \widehat{G}_j(l,m) = \begin{cases} \dfrac{\hat{\psi}_{\frac{l_c}{2^{j+1}}}(l,m)}{\hat{\phi}_{\frac{l_c}{2^j}}(l,m)} & \text{if } l < \frac{l_c}{2^{j+1}} \quad \text{and} \quad m = 0 \\ 1 & \text{if } l \geq \frac{l_c}{2^{j+1}} \quad \text{and} \quad m = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\text{Here,} \quad \hat{G}_j(l,m) = 1 - \hat{H}_j(l,m)$$

In the above given formula set, most of the Radon transforms not have been the invertible transforms for digital images. Meanwhile the Radon transform theory introduced another new interesting topic of transform with by inheriting periodization.

After this invention, Radon Transform has been updated to Slice Support Radon Transform (SSRT), to provide the better support for sliced ridgelet transform. This Slice Support Radon Transform is defined as summations of image pixels over a certain set of "lines." Those lines are defined in a finite geometry in a similar way as the lines for the continuous Radon transform in the Euclidean geometry [17].
The SSRT for sliced ridgelets was customized as shown below:

$$r_k[l] = FRAT_f(k, l) = \frac{1}{\sqrt{p}} \sum_{(i,j) \in L_{k,l}} f[i, j].$$

$$L_{k,l} = \{(i, j) : j = ki + l \pmod{p}, i \in Z_p\}, \quad 0 \leq k < p,$$

$$L_{p,l} = \{(l, j) : j \in Z_p\}.$$

Here, $L_{k,l}$ denotes the set of points that make up a line on the Z^2_p lattice , or, more precisely and i, j are the temp values , p is a prime number and k is the number of vertical lines. The measurable sliced ridgelet co-efficient of an image object f are given by analysis of the Radon transform via:

$$R_f(a,b,\theta) = \int Rf(\theta,t)\psi(\frac{t-b}{a})dt$$

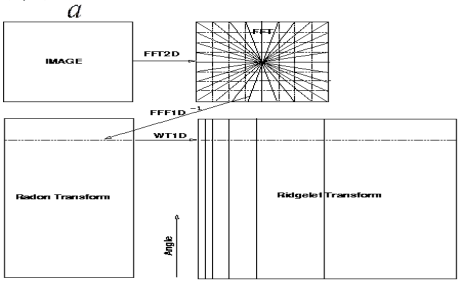


Figure 5 Radon Transform for Sliced Ridgelets

2.3 SLICED RIDGELET TRANSFORM IMPLEMENTATION

The sliced ridgelet transform implementation for digital images at lines, we use this approach as follows

$$L^{\omega}_{[p,q]} = \left\{ (x_1, x_2) \in \mathbb{Z}^2 \middle| |qx_1 - px_2| \leq \frac{\omega}{2} \right\}$$

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

with [p, q] ϵ Z2 the direction of the Radon projection and w, a function of (p, q), the arithmetical thickness. Reveilles introduced the discrete analytical lines defined as 0 <= qx - py + r < w. In this thesis, since we need central symmetry, we chose a variant of the closed discrete analytical lines, defined as 0<= qx – py <= w.

It is easy to see that the closed discrete analytical lines Lw [p, q] have a central symmetry regardless of the value of w. Moreover, the discrete analytical line can easily be extended to higher dimensions as discrete analytical hyper planes.The arithmetical thickness w is an important parameter that controls, among other things, the connectivity of the discrete lines: let's consider the closed discrete analytical line Lw [p, q] and its Euclidean counterpart L[p, q] : qx1 - px2 = 0, then:

- ✶ For w< max (|p| , |q|), Lw [p, q] is not connected;
- ✶ For w = max (|p| , |q|), Lw [p, q] is 8-connected.

This is called the closed naive line. It is directly related to the distance d1 since:

$$L_{[p,q]}^{\max(|p|,|q|)} = \left\{ M \in \mathbb{Z}^2 \middle| d_1\left(M, \mathcal{L}_{[p,q]}\right) \leq \frac{1}{2} \right\}$$
$$\text{with } d_1(A,B) = \left|x_1^A - x_1^B\right| + \left|x_2^A - x_2^B\right|$$

- ✶ For w< max (|p| , |q|), Lw [p, q] is 8 connected;
- ✶ For w = max sqrt(|p| , |q|), Lw [p, q] is 8-connected.

$$L_{[p,q]}^{\sqrt{p^2+q^2}} = \left\{ M \in \mathbb{Z}^2 \middle| d_2\left(M, \mathcal{L}_{[p,q]}\right) \leq \frac{1}{2} \right\}$$
$$\text{with } d_2(A,B) = \sqrt{\left(x_1^A - x_1^B\right)^2 + \left(x_2^A - x_2^B\right)^2}$$

These results are direct consequence of a well-known result in discrete analytical geometry and more recent studies on distances.The fact that these lines can be defined with help of distances makes a direct link with mathematical morphology. We use the Fourier domain for the computation of Fast Fourier Radon transform: Fourier coefficients of s are extracted along the discrete analytical line L^w[p, q].

$$P_{[p,q]}^{\omega} s = \bigcup_{k \in \mathbb{Z}+} \hat{s}(f_1^k, f_2^k) \text{ such that } \left|q f_1^k - p f_2^k\right| \leq \frac{\omega}{2}$$

and we take the 1-D inverse FFT of Pw [p, q]s on each value of the direction [p, q]. Formally, our discrete analytical Radon transform is defined by:

$$R^{\omega} s([p,q], b) = \sum_{k=0}^{K-1} P_{[p,q]}^{\omega} s(k).e^{2\pi j \frac{k}{K} b} \text{ with } K \text{ length of } L_{[p,q]}^{\omega}$$

We must dene the set of discrete directions [p, q] in order to provide a complete representation. The set of line segments must cover the entire square lattice in the Fourier domain. For this, we define the directions [p, q] according to pairs of symmetric points from the boundary of the 2-D discrete Fourier spectra as shown in figure 6.

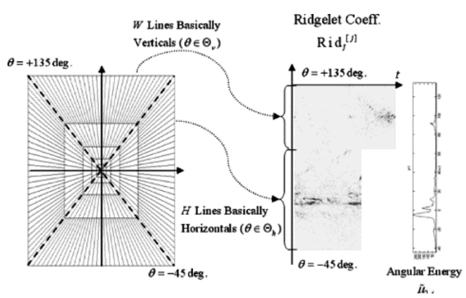


Figure 6 Sliced Ridgelet Transformation for line Singularities

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

PROPOSED ALGORITHM -SLICED RIDGELET DE_NOISING ALGORITHM

Begin
Input: digital image corpus with noise
Output: de-noised digital image corpus
Process:
Step1: Start image partition as horizontal and vertical RxR blocks
Step2: Arrange the vertical overlapping for adjacent block as R/2xR
Step3: Arrange the horizontal overlapping for adjacent block as RxR/2
Step4: forEach (block: RxR) {

- *Apply image slicing*
- *Get smaller number of coefficients*
- *Apply FastFourierTransform (FFT)*
- *Apply Radon Transform*
- *Set Threshold value*
- *Run sliced ridgelet transform*

}
Step5: Collect the same location pixel values at donoising image
Step6: Generate process phase wise result report and display them
End

We call this algorithm as Sliced RidgeletShrink, while the algorithm using the ordinary RidgeletShrink. The computational complexity of Sliced RidgeletShrink is similar to that of RidgeletShrink by using the scalar wavelets. The only difference is that we replaced the 1D ridgelet transform with the 1D dual-tree sliced ridgelet transform. The amount of computation for the 1D dual-tree sliced ridgelet is twice that of the 1D scalar wavelet transform. However, other steps of the algorithm keep the same amount of computation.Our experimental results show that sliced RidgeletShrink outperforms VisuShrink, RidgeletShrink, and wiener2filterfor all testing cases. Under some case, we obtain 1.30 dB improvements in PSNR over RidgeletShrink. The improvement over VisuShrink is even bigger for de-noising all images. This indicates that Sliced RidgeletShrinkis an excellent choice for de-noising natural noisy images. This whole process is explained in detail of the experiments section

III. SIMULATION RESULTS

The In this section we discuss about the image de-noising experiments in detail with our proposed sliced ridgelet transform methodology. In these experiments, we simulate noisy images by corrupting the 512 x 512 textured grass images with 10 different realizations of WGN with standard deviation 25. The noisy images are then de-noised with various existing methodologies and our sliced ridgelet transform environment.we implement VisuShrink, RidgeletShrink, SlicedRidgeletShrink and wiener2. VisuShrinkis the universal soft-threshold denoising technique. The wiener2 function is available in the MATLAB Image Processing Toolbox, and we use a 5×5 neighborhood of each pixel in the image for it. The wiener2 function applies a Wiener filter (a type of linear filter) to an image adaptively, tailoring itself to the local image variance.The experimental results in PSNR are shown is for de-noising Lena image for different image partition block sizes by using ComRidgeletShrink. It can be seen that the partition block size of 32×32 or 64×64 is our best choice as shown in figure 7. In MRI Scan experiment, for different noise levels and a fixed partition block size of 32×32 pixels. The first column in these tables is the PSNR of the original noisy images, while other columns are the PSNR of the de-noised images by using different donoising methods along with our proposed sliced ridgelet transform and the result is as shown in below figure 7.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

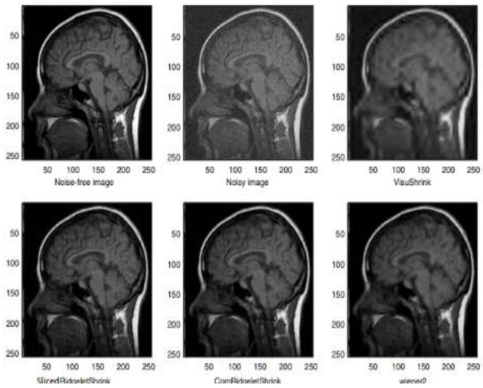
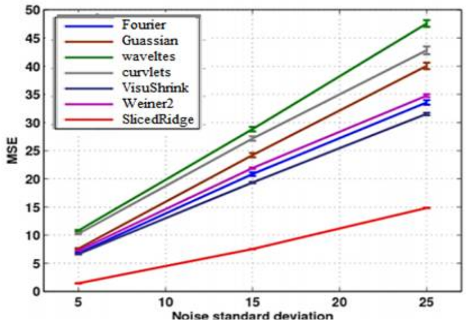


Figure 7 MRI Scan Experiment with various image de-noising methodologies,



Noisy image	VisuShrink	RidgeletShrink	SlicedRidgeletShrink	wiener2
34.12	29.49	36.67	**37.19**	30.96
28.10	26.31	32.51	**33.13**	30.09
24.58	24.77	30.23	**30.79**	29.04
22.08	23.85	28.63	**29.21**	28.01
20.14	23.24	27.39	**28.00**	27.07
18.56	22.83	26.39	**27.03**	26.22

From Tables 1 we can see that SlicedRidgeletShrink out performs VisuShrink, the ordinary RidgeletShrink, andwiener2for all cases. VisuShrink does not have any donoising power when the noise level is low. Under such a condition, VisuShrink produces even worse results than the original noisy images. However, SlicedRidgeletShrink performs very well in this case. For some case, SlicedRidgeletShrink gives us about 1.30 dB improvements over the ordinary RidgeletShrink.From figure we compare the de-noising performance for various methods for the synthetically generated stripes image containing multiple exact replicas of each line singularity.

Figure 8 MRI Scan Image donoising comparison, Table 1 MRIScan Comparison with various donoising techniques

For strong noise, the non-local methods, namely VisuShrink, Weiner2 and Guassian, Sliced Rigelet clearly outperform the local approaches. High levels of redundancy as well as low patch complexity result in our bounds predicting a very small lower bound even for quite strong noise levels.Comparing performances of the state-of-the-art methods to the bounds allows us to gauge the room for improvement in denoising performance of any given image. As a result, the bounds for natural images are usually much higher. The room for improvement for natural images can also be seen to be much lower than those for the synthetic images used in our study. Even for these natural images, the plots at low SNRs can be segregated into two regions.

From the above discussion, it becomes apparent that image denoising as a problem is not dead – yet. This is particularly true for the class of smoother images containing sufficiently large number of repeating patterns. On the surface, this may appear to be in direct contradiction to the observations in where Levin and Nadler compared the bounds to the best denoising methods and concluded that the performance of current non-parametric approaches cannot be improved upon, unless considerably larger patches are used.

IV. Conclusion and Future Work

In this paper, we study image de-noising by using sliced ridgelets. It tries to remove the Gaussian white noise presented in the noisy images and also alleviates the limitations of wavelet and general ridgelet problems. Recent trends in ridgelet transforms proven that they are better than wavelet transforms to reduce the noise in images. This thesis concentrates on improvising the features of ridgelet transform to perform well than what it stands. As per our concern there is a wide research area and scope is still waiting for research concentration in ridigelet transforms.

ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 6, June 2016

This research work compares the accuracy and scalability of image de-noising with other popular approaches like wavelets, curvlets and some other inter-relevant technologies. We test our new denoising method with several standard images with Gaussian white noise added to the images. A very simple hard thresholding of the complex ridgelet coefficients is used. Experimental results show that complex ridgelets give better denoising results than VisuShrink, wiener2, and the ordinary ridgelets under all experiments. We suggest that ComRidgeletShrinkbe used for practical image donoising applications. Experimental results are proven that the sliced ridgelet approach is having the better performance than the other popular techniques.

Future work: Future work will be done by considering sliced ridgelets in curvelets image de-noising. Also, complexridgelets could be applied to extract invariant features for pattern recognition.
The computational cost of the sliced ridgelet transform is bit higher than that of ridgelets, especially in terms of 3D problems. We set the goal of reducing the computational cost of sliced ridgelets than general ridgelets is the another area of future research.

REFERENCES

1. V.Krishna Naik, Prof.Dr.G.Manoj Someswar, R.B. Dayananda "Sliced Ridgelet Transform for Image De-noising" IOSR Journal of Computer Engineering (IOSR-JCE), e-ISSN: 2278-0661, p- ISSN: 2278-8727Volume 14, Issue 1 (Sep. - Oct. 2013), PP 17-21;
2. Jean-Luc Starck, Emmanuel J. Candès, and David L. Donoho "The Curvelet Transform for Image De-noising" IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 11, NO. 6, JUNE 2002.
3. E. Cand`es, D. Donoho, Ridgelets: A key to higher-dimensional intermittency?, R. Soc. Lond. Philos. Trans. Ser. A Math. Phys. Eng. Sci., 357, 2495-2509 (1999).
4. B. Zhang, J. Fadili, J. Starck, Wavelets, ridgelets, and curvelets for Poisson noise removal, IEEE Trans. Image Process., 17 (7), 1093-1108 (2008).
5. J. Ma, M. Fenn, Combined complex ridgelet shrinkage and total variation minimization, SIAM J. Sci. Comput., 28 (3), 984-1000 (2006).
6. R. Coifman and D. Donoho. Wavelets and Statistics, chapter Translation invariant de-noising, pages 125–150. Springer-Verlag, 1995.
7. Hyeokho Choi and Richard G. Baraniuk. Multiple Wavelet Basis Image Denoising Using Besov Ball Projections. IEEE Signal Processing Letters, 11, no. 9: 717 – 720, 2004.
8. S. Barber and G. P. Nason. Real nonparametric regression using complex wavelets. J. Roy. Stat. Soc. B, 66, no. 4: 927 – 939, 2004.
9. H. Chauris, T. Nguyen, Seismic demigration/migration in the curvelet domain, Geophysics, 73 (2), S35-S46 (2008).
10. A. Antoniadis and J. Fan. Regularization of wavelet approximations. Journal of the American Statistical Association, 96, no. 455:939 – 955, 2001.
11. I. Adam, C. Nafornita, J.-M. Boucher, and Al. Isar. A New Implementation of the Hyperanalytic Wavelet Transform. In Proceedings of IEEE International Symposium ISSCSŠ07, Iasi, Romania , 2007.
12. Abdourrahmane M. Atto, Dominique Pastor, and Gregoire Mercier. Smooth Sigmoid Wavelet Shrinkage For Non-Parametric Estimation. In IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP, Las Vegas, Nevada, USA, 30 march - 2008.
13. E. Cand`es, L. Demanet, Curvelets and Fourier integral operators, C. R. Math. Acad. Sci.Paris, 336 (5), 395-398 (2003).
14. L. Demanet, L. Ying, Curvelets and wave atoms for mirror-extend images, Proc. SPIE Wavelets XII, San Diego, August 2007.
15. A. Cordoba, C. Fefferman, Wave packets and Fourier integral operators, Comm. Partial Differential Equations, 3, 979-1005 (1978).
16. GM.N. Do, M. Vetterli, The finite ridgelet transform for image representation, IEEE Trans. Image Process. 12 (1) (2003) 16–28.E.J.
17. Candes, Ridgelets: theory and applications, Ph.D. Thesis, Technical Report, Department of Statistics, Stanford University, 1998.

BIOGRAPHY

Shri Mr.VANKDOTH KRISHNANAIK, Ph.D - Research Scholar from**Mewar University**, Rajasthan, India.And Currently working as Assoc. Professor, in the Department of Electrical & Computer Engineering, College of Engineering & Tech, Aksum University, Ethiopia. He completed **B.E (ECE) from C.B.I.T, Osmania University, Hyderabad in 1999 and M.Tech (Systems & Signal Processing) from J.N.U.C, J.N.T.U Hyderabad in 2005**. He is having 16+ years of relevant work experience in **Academics, Teaching, Industry & Research**. And utilizing his teaching skills, knowledge, experience and talent to achieve the goals and objectives of the Engineering College in the fullest perspective. He has attended more than 6 national and international conferences, seminars, workshops and Published 5 Books for Engineering and Technology. He is also having to his credit more than 20 research articles and paper presentations which are accepted in national and international conference proceedings. His areas of Research in Digital signal processing, Image processing, speech processing, Digital Systems.