DENOISING OF SAR IMAGES USING INTEGRATED REDUNDANT CURVELET TRANSFORMATION WITH EMD

A.Ravi[1], Dr. P.V.Naganjaneyulu[2], Dr.M.N. Giriprasad[3]
[1]Research Student, JNTUH, Email: ravi.ajmeera@gmail.com
[2]Principal, MVRCOE, Paritala, india ,Email: pvnaganjaneyulu@gmail.com
[3]Head Of ECE, JNTUA, Anantapur, india, Email: mahendragiri1960@gmail.com

ABSTRACT: As the progressive work is on noise removal from SAR (synthetic aperture images) images an efficient noise removal technique was proposed especially removing SPECKLE noise. This paper represents an improved denoising technique by redundant curvelet transformations for removing noise from SAR images. This improves information provided by the image and reducing noise rate in the same. This helps in preserving the images in multi resolution analysis and even filtering the curved architectures in the images. Various error calculation parameters were observing on these redundant curvelet transformation in combination with Empirical mode decomposition filtered image by indicating the best resultant value in the tabular form provided below in results. These observations were executed and results were simulated in MATLAB.

INDEX TERMS: SAR, SPECKLE, REDUNDANT CURVELET TRASNFORMATION, ERROR CALCULATION PARAMETERS.

I. INTRODUCTION

Speckle noise exists naturally to a picture and will be great known as granular clamour. This degrades that calibre about a picture. Lion's share of the surface pictures with greatly harsh surface middle of the road with this commotion this will likewise watch previously, ultimo callous pictures. On translate those sar pictures it is exceptionally troublesome for the spot clamor. So, for uprooting those commotion a number perceptions ahead different filters need undergone also not great in evacuating the clamour about picture akbarizadeh, g. (2012).

Every last one of filters that bring been specified over were beneficial at de-speckling for sar pictures in any case they will give main low recurrence content of a picture it doesn't preserve the high back data. In place with succeed this issue non neighborhood intend methodology need been acquainted. Additional recently, dot decrease strategies dependent upon the "non-local intends" (nlm). It will be a data-driven dissemination component that might have been presented by buades et al. Clinched alongside baselice, f ; ferraioli,g (2014).

Similarly as an outcome about object identification furthermore area about investment (roi) for sar images, these might have a extreme test actually to an expert, same time programmed calculations dedicated of the same assignments that would not simply dependable enough for practically of the provisions.

For this reason, concentrating on about sar pictures also lessening different noises furthermore progressed spatial channel systems is expanding. Indeed, spatial sifting strategy loves innovation suggested by deledalle, c's. A ;denis,l ; poggi, g ; tupin, f ; verdoliva. L. (2014), bring been promptly connected on sar pictures deliaing xiang ; tao tang ; canbin hu ; yu li ; yi su (2014), on acquire great effects.

However, spatial sifting methodologies in intend sifting or normal filtering, savitzky filtering, average filtering, reciprocal channel also wiener filters required been suffice for loosing edges data. It need been demonstrated that it's an basic furthermore capable technique for advanced picture denoising.

There are different happened done wavelet conversion interleaving those odds whether state is curvy in this way to decrease this impact curvelet change will be recommended. Here matching the idea from claiming excess wavelet change another technique is actualizing i. E, excess curvelet conversion m. J. Fadili , and j. -l. Starck (2007).

The square outline will be demonstrated for area iii under excess curvelet conversion. We received those curvelet era toolmaker starting with www. Curvelettoolbox. Org. This paper mostly focussing on the decrease for clamour from a picture toward utilizing an ordinary mixture change those effects unmistakably demonstrates those techno babble effectiveness previously, diminishing those unwanted majority of the data.

Will enhance these comes about confirmation iqa need been helped for slip or transform done picture following filtration alternately change will be preparing for this level. Full-reference (fr) iqa routines depend on the accessibility of a clean undistorted reference picture will assess the caliber of the test test. In the issue from claiming fake identification tended to in this worth of effort such an reference picture may be unknown, concerning illustration the identification framework main need entry of the information test. In place will circumvallated this limitation, those same method as of now effectively utilized to picture control identification also for steganalysis might have been executed. Similarly as demonstrated over fig. 2, the information grey-scale picture i (of size n × m) may be separated with an low-pass gaussian part ($\sigma = 0.5$ and span 3×3) in place with produce a smoothen rendition. Then, the calibre between both pictures as stated by those comparing full-reference iqa metric may be registered.

TABLE 1
LIST OF THE 11 IMAGE QUALITY MEASURES (IQMS) IMPLEMENTED IN THE PRESENT WORK AND USED FOR IMAGE QUALITY. ALL THE FEATURES WERE EITHER DIRECTLY TAKEN OR ADAPTED FROM THE REFERENCES GIVEN.

#	TYPE	ACRONYM	NAME	REF	DESCRIPTION
1	FR	MSE	Mean Squared Error	[7]	$MSE(K,\widehat{K}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(K_{i,j}-\widehat{K}_{i,j})^2$
2	FR	PSNR	Peak Signal to Noise Ratio	[8]	$PSNR(K,\widehat{K}) = 10\log\left(\frac{\max(K^2)}{MSE(K,\widehat{K})}\right)$
3	FR	SNR	Signal to Noise Ratio	[9]	$SNR(K,\widehat{K}) = 10\log\left(\frac{\sum_{i=1}^{N}\sum_{j=1}^{M}(K_{i,j})^2}{N.M.MSE(K,\widehat{K})}\right)$
4	FR	SC	Structural Content	[10]	$SC(K,\widehat{K}) = \frac{\sum_{i=1}^{M}\sum_{i=1}^{N}(K)^2}{\sum_{i=1}^{M}\sum_{i=1}^{N}(\widehat{K})^2}$
5	FR	MD	Maximum Difference	[10]	$MD(K,\widehat{K}) = \max(\lvert K-\widehat{K}\rvert)$
6	FR	AD	Average Difference	[10]	$AD(K,\widehat{K}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}(K_{i,j}-\widehat{K}_{i,j})$
7	FR	NAE	Normalized Absolute Error	[10]	$NAE(K,\widehat{K}) = \frac{\sum_{i=1}^{M}\sum_{i=1}^{N}(K-\widehat{K})}{\sum_{i=1}^{M}\sum_{i=1}^{N}(K)}$
8	FR	RAMD	R-Averaged MD	[7]	$RAMD(K,\widehat{K},R) = \frac{1}{N}\sum_{r=1}^{R} max\lvert K-\widehat{K}\rvert$
9	FR	SSIM	STRUCTUTRAL SIMILARITY INDEX	[10]	SEE [12]
10	FR	TED	Total Edge Difference	[11]	$TED(K,\widehat{K}) = \frac{1}{NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\lvert K_{i,j}-\widehat{K}_{i,j}\rvert$
11	FR	TCD	Total Corner Difference	[11]	$TCD(K,\widehat{K}) = \frac{\lvert N_{cr}-\widehat{N}_{cr}\rvert}{\max(N_{cr},\widehat{N_{cr}})}$

The rest of the paper is organised as section II briefing curvelet transformation with algorithm and mathematical approach, section III briefs Proposing methodology i.e., Redundant curvelet transformation Shiyon Cui, Dumitru, Datcu. M (2013). Section IV explains the experimental results of various filters and tabular forms indicate the error measurements of the system. Finally section V concludes the paper with the best values obtained D.L. Donoho and I.M. Johnstone (1994)..

II. CURVELET TRANFORMATION

ALGORITHM

TASK: SPECKLE DENOISING OF SAR IMAGES USING CURVELET TRANSFORMATION
INPUT PARAMETERS: Number of resolution levels I, minimum block size is Bmin.
Compute curvelet with I scales to get the stabilized wavelet sub-bands Wj.
Set B1 = Bmin
For i = 1to I do

1. Partition the subband *wj* with blocks of side length B*j* .
2. Apply the digital ridgelet transform to each block to obtain the stabilized curvelet coefficients *wj*.
3. Detect the significant stabilized curvelet coefficients to obtain M.
4. if *j* modulo 2 = 1 then B*j*+1 = 2B*j*
5. else B*j*+1 = B*j*
6. end if

Reconstruction: Apply the HSD iterative reconstruction with the curvelet multi-resolution support to get the final estimate.

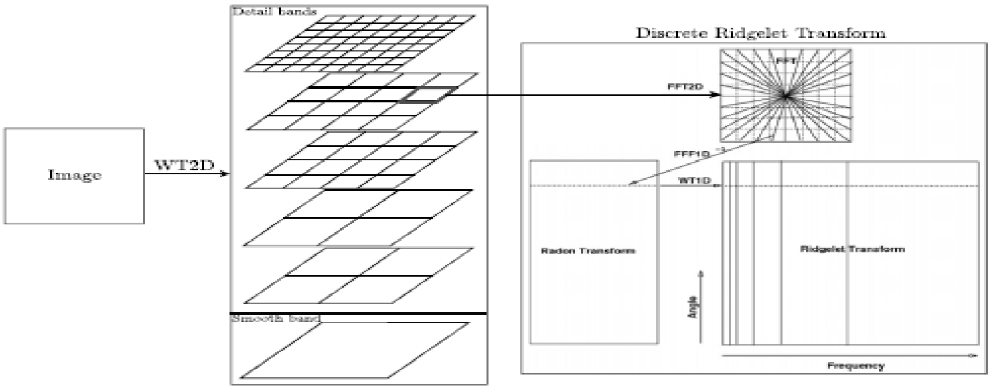

Figure 1: Flow chart for discrete curvelet transformation. This flow diagram indicates each block of image is applied by Ridgelet transformation after decomposing the image into sub-bands.

III. REDUNDANT CURVELET TRANSFORMATION

TASK: SPECKLE DENOISING OF SAR IMAGES USING INTEGRATED REDUNDANT CURVELET TRANSFORMATION

INPUT PARAMETERS: Number of resolution levels I, minimum block size is Bmin.

Compute curvelet with I scales to get the stabilized wavelet sub-bands Wj.

Set B1 = Bmin

For i = 1to I do

1. Partition the subband *wj* with blocks of side length B*j* .

2. Apply the digital ridgelet transform to each block to obtain the stabilized curvelet coefficients *wj*.

3. Detect the significant stabilized curvelet coefficients to obtain M.

4. if *j* modulo 2 = 1 then B*j*+1 = 2B*j*

5. else B*j*+1 = B*j*

6. end if

7. Bj* = Bj+Bj

8. continue step 1 to 6

8. end For

9. Applying inverse curvelet transform

Reconstruction: Apply the HSD iterative reconstruction with the curvelet multi-resolution support to get the final estimate.

These features compute the distortion between two images on the basis of their pixelwise differences Maarten Jansen (2001), Xingyu Fu ; Hongjian You ; Kun Fu (2012).. Here we include: Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Structural Content (SC), Maximum Difference (MD), Average Difference (AD), Normalized Absolute Error (NAE). The formal definitions for each of these features are given in Table I.

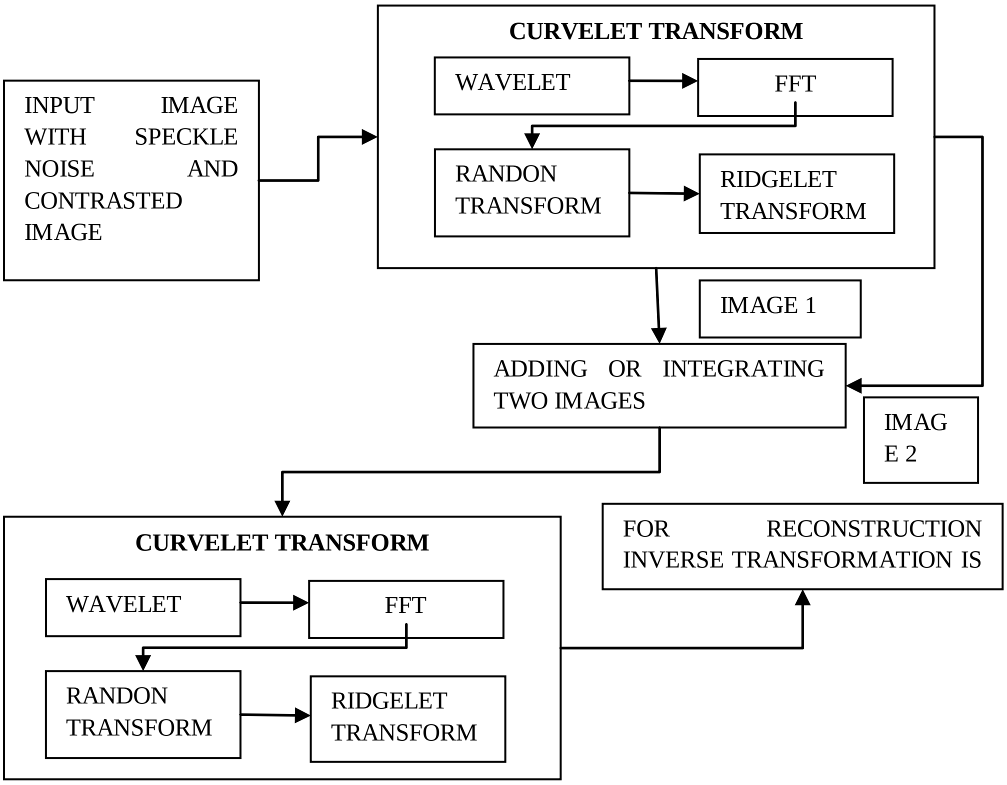

FIGURE 2. BLOCK DIAGRAM of proposed scheme

IV. REDUNDANT CURVELET TRANSFORMATION WITH EMPIRICAL MODED DECOMPOSITION

EMD is a time frequency data driven with adaptive decomposition mode of a signal D.L. Donoho and I.M. Johnstone (1995), J. L. Starck, D.L Donoho, E.J Candes (2003).. This possesses sifting algorithm converges to AM/FM modulation with intrinsic mode function. It consist of three stages 1) Tracing local minima and maxima values, 2) Envelope or tracing the edges of the Images and finally 3) Calculating the details and equalising the output to IMF's. Details will calculated as $D = I - \left(\frac{1}{2}\right) * (Emin + Emax)$ (1).

The resultant algorithm in combination with RFDCT is showcased below:

TASK: SPECKLE DENOISING OF SAR IMAGES USING INTEGRATED REDUNDANT CURVELET TRANSFORMATION EMPIRICAL MODE DECOMPOSIITON

INPUT PARAMETERS: Number of resolution levels I, minimum block size is Bmin.
Compute curvelet with I scales to get the stabilized wavelet sub-bands Wj.
1. Let$\hat{I} = I$.
2. Trace Maxima and minima values from $\hat{I}$.
3. Interpolate and extract envelope for minima and maxima values as E_{min} and $E_{max.}$
4. Details 'D' has to be extracted from envelope using eq (1).
5. Repeat 2-4 till D becomes the IMF of the Input image I and will be given as input to RFDCT
Set B1 = Bmin
For i = 1to I do
1. Partition the subband *wj* with blocks of side length B*j* .
2. Apply the digital ridgelet transform to each block to obtain the stabilized curvelet coefficients *wj*.
3. Detect the significant stabilized curvelet coefficients to obtain M.
4. if *j* modulo 2 = 1 then B*j*+1 = 2B*j*
5. else B*j*+1 = B*j*
6. end if
7. Bj* = Bj+Bj
8. continue step 1 to 6
8. end For
9. Applying inverse curvelet transform
Reconstruction: Apply the HSD iterative reconstruction with the curvelet multi-resolution support to get the final estimate.

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V. EXPERIMENTAL RESULTS

TABLE 2. CURVELET TRANSFORM

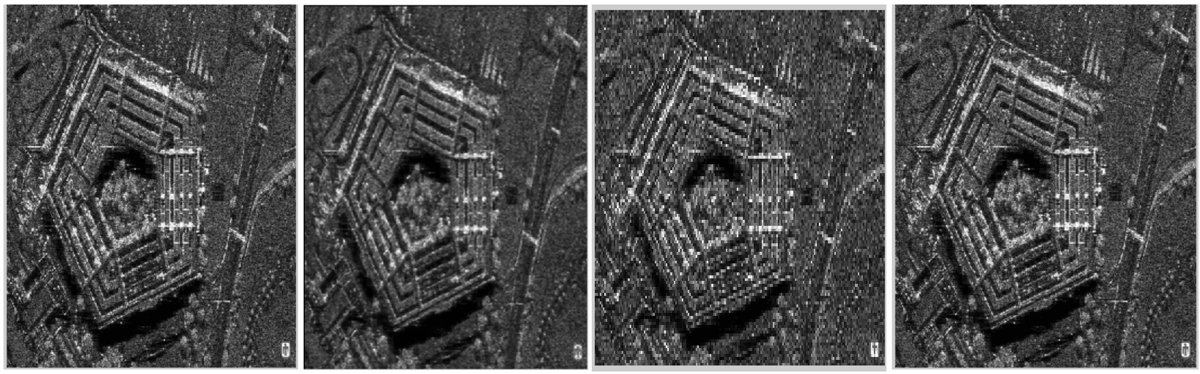
CURVELETES					
	CAPITAL	CHINA LAKE	JEFF MEM	LIBCONG	PENTAGON
MSE	0.0034	0.0032	0.0653	0.0504	0.0548
PSNR	56.8	57.3147	27.2873	29.8783	29.0457
SNR	3.0637	3.5471	1.163	1.1205	1.022
SC	8.31E+02	4.55E+02	5.58E+02	6.00E+02	1.32E+03
MD	0.0201	0.0616	0.2665	0.2161	0.2352
AD	-6.01E-17	-8.43E-17	-0.0099	-0.0049	-0.0097
NAE	0.108	0.4092	0.7915	0.8145	0.7911
TED	14.1368	10.5975	38.6853	39.22.95	70.8003
TCD	-0.0135	-0.0109	0.2492	0.0966	0.1472
SSIM	1	1	0.9995	0.9997	0.9998
Entropy	6.8429	6.3374	7.0911	7.0454	6.812
Corr	0.93296	0.8876	0.9277	0.89948	0.85347
Std	0.4215	0.3269	0.5296	0.4246	0.3839

TABLE 3. INTEGRATED REDUNDANT CURVELET TRANSFORM

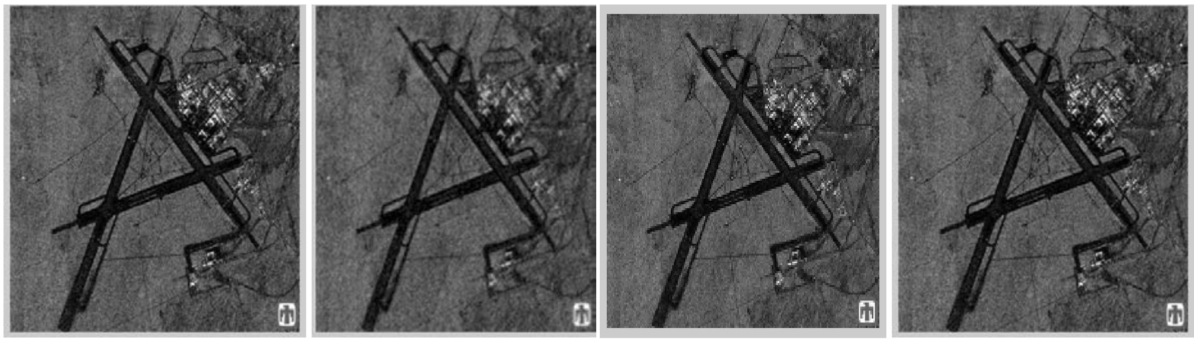
REDUNDANT CURVELET					
	CAPITAL	CHINA LAKE	JEFF MEM	LIBCONG	PENTAGON
MSE	0.1018	0.0073	0.1494	0.0948	0.0518
PSNR	56.4744	85.1288	58.1268	59.3785	66.4429
SNR	4.7835	8.0948	5.3418	5.4546	5.9682
SC	1.80E+12	9.80E+12	-2.43E+11	-2.54E+12	-5.55E+13
MD	0.0597	0.0641	0.0743	0.0753	0.0814
AD	-0.02	-0.0051	-0.0242	-0.192	-0.0142
NAE	0.3342	0.4662	0.404	0.421	0.5036
NXC	-2.20E+04	-6.31E+03	4.52E+04	-1.15E+05	-2.81E+04
TED	12.9654	12.8322	14.7741	13.4251	16.6378
TCD	0.0168	0.006	-0.0342	-0.0784	-0.0826
SSIM	0.9998	0.9999	0.9997	0.9998	0.9998
Entropy	6.8429	6.3374	7.0911	7.0454	6.812
Corr	0.93296	0.8876	0.9277	0.89948	0.85347
Std	0.4215	0.3269	0.5296	0.4246	0.3839

TABLE 4. INTEGRATED REDUNDANT CURVELET TRANSFORM WITH EMPIRICAL MODE DECOMPOSITON

REDUNDANT CURVELET + EMPIRICAL MODE DECOMPOSITION					
	CAPITAL	**CHINA LAKE**	**JEFF MEM**	**LIBCONG**	**PENTAGON**
MSE	**0.01718**	**0.00173**	**0.011494**	**0.00148**	**0.0051**
PSNR	**56.9244**	**85.5788**	**58.5768**	**59.8285**	**66.8929**
SNR	**5.8935**	**9.2048**	**6.4518**	**6.686**	**7.01682**
SC	**1.80E+12**	**9.80E+12**	**-2.43E+11**	**-2.54E+12**	**-5.55E+13**
MD	**0.0597**	**0.0641**	**0.0743**	**0.0753**	**0.0814**
AD	**-0.02**	**-0.0051**	**-0.0242**	**-0.192**	**-0.0142**
NAE	**0.3342**	**0.4662**	**0.404**	**0.421**	**0.5036**
NXC	**-2.20E+04**	**-6.31E+03**	**4.52E+04**	**-1.15E+05**	**-2.81E+04**
TED	**8.9654**	**8.8322**	**9.7741**	**10.4251**	**13.6378**
TCD	**0.0168**	**0.006**	**-0.0342**	**-0.0784**	**-0.0826**
SSIM	**0.9999**	**0.9999**	**0.9999**	**0.9999**	**0.9999**
Entropy	**7.1022**	**7.8364**	**8.02**	**8**	**7**
Corr	**0.93296**	**0.8876**	**0.9277**	**0.89948**	**0.85347**
Std	**0.4215**	**0.3269**	**0.5296**	**0.4246**	**0.3839**



A **B** **C** **D**



A **B** **C** **D**

Figure 3 for result show case we use capital and china lake sar images. A-Original image, B- Curvelet and C- Integrated Redundant curvelet transformation, D- Integrated Redundant Curvelet Transform with EMD.

VI. CONCLUSION

The principle distinction done applying excess curvelet change demonstrates those change from claiming picture calibre by analyzing those comes about following applying different sorts from claiming filtration what's more conversion strategies. This picture calibre investigation parametric after effect the best method will be excess curvelet change n consolidation with experimental mode decay gives most extreme diminishment of commotion from the pictures also these comes about were compared with curvelet transformations what's more excess curvelet transformations..

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AUTHOR BIOGRAPHY

A. Ravi received his Bachelors degree in ECE from JNT University, and received his M.Tech from JNTU Kakinada. He is now a research scholar under the guidance of **Dr. P.V. Naganjaneyulu & Dr. M.N. Giriprasad**. His current research interest includes Satellite and SAR image processing.

Dr. P.V. Naganjaneyulu received Ph. D in Communications from JNTU Kakinada University. And he is currently professor and Principal, Department of ECE in PNC & VIJAI Institute of Engineering & Technology, Repudi, Guntur dist., he was specialized in communication and signal processing, he published 30 journal papers and 10 conference papers. His current research area of interest is communications, signal processing and image processing. He is a member of IETE.

Dr. M.N. Giriprasad Received the B.Tech degree from JNTUA, Andra pradesh, M.Tech from SVU, Tirupathi and Ph.D. from JNTUH. He is now working as Professor & HOD in Dept. of ECE at JNTU College of engineering Ananthapur. His current research interests includes Wireless communications, Bio medical Instrumentation and image processing. He is a member of ISTE, IE & NAFE.