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Noise Reduction and Restoration of Image Using SD-VMRCT

[1]Ravi Ajmeera
Research Scholar, Department of ECE, Jawaharlal Nehru Technological University, Hyderabad, Telangana, India.

[2] Dr. P.V. Naganjaneyulu
Principal & Professor of ECE, MVR College of Engineering & Technology, Paritala(V), Krishna Dist. Andhra Pradesh, India.

[3] Dr. M.N. Giriprasad
Professor of ECE, Jawaharlal Nehru Technological University, Anantapur Saradha Nagar, Anantapur, Andhra Pradesh, India.

[1]ORCID: 0000-0002-6836-1959, [1]Scopus Author ID: 56335854200

Abstract

Reducing speckle noise by smoothing images with contrast enhancement in SAR images is our major task. The Noise reduction and contrast enhancement are two different zones in digital image processing. But conventional methods are not effective in producing these two approaches in a single context, so in our approach fusion based contrast enhancement with the effective iterative procedure for noise reduction applied on SAR images was considered with a well-defined architecture. In Multi-resolution analysis smoothing filter and SD (Sparse driven) approaches were combined to perform noise reduction and contrast enhancement of images in this novel scheme. Sparse Driven -Variational Mode Redundant Curvelet Transform (SD-VMRCT) minimizes the noise in two steps first is a fusion of curvelet transform coefficients. In this phase, curvelet transform minimizes error rate caused by speckle noise but that is not effective in reducing the variance effect(noise) in SAR images and the second phase is sparse driven using iterative intrinsic mode function based on weight developed for minimizing noise and obtaining contrast-enhanced curvelet coefficients with minimizing the effect of sparse in the image.

Keywords: Speckle noise, contrast, SAR images, Multiresolution analysis, smoothing filter, RDCT, VMRCT, and SD

INTRODUCTION

Noise reduction in SAR images is the Most important Application in Remote sensing. Previously various approaches were developed for reducing the multiplicative noise in synthetic Aperture RADAR (SAR) images. Clustering, Multi-resolution, class filters, and anisotropic diffusion are used for reducing the image noise for different values of σ (noise variance) AWGN, an additive signal-dependent noise model, Speckle noise, and Rayleigh noises were applied on SAR images this leads to non-local means of pixels in images. Similar spatial structure nonlocal neighboring pixels geometrically nearer to each other are used to perform weight. In [1] the author suggests clustering with PCA results [2] minimizing the noise ratio image detail preservation. But numerically these values were not efficient and needs to be rectified.

Some schemes are also applied to reduce multiplicative noise for different variance values [3] and result in a high definition of edge identification but have an iterative complex process i.e., Bayesian filtration was carried out. By enhancing the characteristics of edge identification in SAR images will help in identifying the boundaries of different areas and even helps in categorizing land covered.

BM3D (Block Matching 3 dimensional) approach helps in identifying the targets using canny edge detector and de-speckling the image. Performance parameters show the inefficiency of BM3D [1-5] through MSE (mean Square error) and Standard deviation. This helps in identifying edges and dots effectively but needs to be enhanced in contrast and brightness of the images.

Redundant curvelet (RDCT) demonstrates filtration for noisy images using both directional and angular filtration processes to the compressor eliminate speckle noise [6]. This technique can be most helpful in identifying the objects in a dark arena and also helps for medical images.

LITERATURE REVIEW

Table 1: A Literature review on different schemes for de-noising SAR images.

TITLE	APPROACH	RESULT
SAR Image De-noising via Clustering-Based Principal Component Analysis [1]	LMMSE based PCA for reducing speckle noise in images. Apart from this, adaptive signal dependent noise also represented [1].	Error rate minimized according to the practical proof and has low rate of information with blur in the recovered image [6-12]
SAR Image Despeckling Using Data-Driven Tight Frame [10]	Logarithmically transformed image with SVD results in attaining the denoising the image.	PSNR of 25.83db for a maximum noise image. This needs to be upgraded and this was rectified in [1-4, 6, 13]
QMCTLS: Quasi-Monte Carlo Texture Likelihood Sampling for Despeckling of Complex Polarimetric SAR Images [11]	Quasi-monte Carlo sampling with probabilistic similarity approach is focused on Despeckling the noise of an image.	It depends on texture area of an image. Irregular objects were not identified clearly. This results not complete elimination of speckle noise from SAR images.
Radar/SAR Image Resolution Enhancement via Unifying Descriptive Experiment Design Regularization and Wavelet-Domain Processing [14]	Wavelet based image resolution enhancement with Despeckling the image based on Super-resolution with sparse representation.	This results in high information carrier with low noise rate but had low contrast values this results in error information zone. To rectify this a novel scheme of approach is carried in section Scheme of Approach.

METHODOLOGY

Noise reduction in SAR images results in blurring due to filtration and minimizing the information of an image. Since filtration of the coefficients in an image images will generate a high number of smoothing coefficients, this causes the blurring nature of the images [1]. The performance parameters like PSNR, MSE will never show a value of growth. To avoid these ineffective schemes we moved to transformations, here minimization of coefficients results in minimizing the error rate in the image caused by speckle noise. For minimizing the error rate and blurring image coefficients we observed many transforms such as FOURIER, COSINE, WAVELET, RIDGELET, CURVELETS and for additional smoothing operation, we also depend on INTERENSIC MODE FUNCTION. We observed a range of increase in the performance metrics all the time. But were not able to achieve the maximum rate that satisfies the error minimization and enhancing the information in an image. For this reason, we represent a novel algorithm for enhancing the characteristics and information in an image and minimizing the coefficients for minimizing the error rate.

Since speckle noise(SN) is a multiplicative noise in which the randomized conditions will reduce the image information and creates more blurring in image coefficients after de-speckling image 'I'. The coefficients (I(x, y), where x and y are spatial coordinates) will represent the image intensity of pixels, but due to SN the intensity of image coefficients will change and result in no effect with normal filtration and transformation approaches. So, to reduce the coefficients a Redundant approach of filtration and to enhance the characteristics of 'I' fusion rule based on resolution are proposing.

So here for filtration of images, multi-resolution transform was used but was not helpful in enhancing the image characteristics. As per the consideration of decomposition approach in Curvelet transform comprised with two windows i) Scaling window and ii) Angular window. The combination these two windows will result in enhanced image coefficients. But is very unstable in the condition of speckle noise, because the smoothing characteristics will reduce image sharpen coefficients and results in a blurred image. Even though it produces an effective performance metrics due to blurring nature in an image we are intended to modify the coefficients of curvelet transform for enhancing the characteristics of an image.

To modify the curvelet coefficients we need discuss how curvelet generates the coefficients using scale window and angular window. Then how fusion helps reduce the smoothing nature of the coefficients of the decomposed images with elaborative increment in the noise of the coefficients. In this context of approach firstly coefficient identification for curvelet transform was considered from [2].

In curvelet transform for decomposition pyramidal filter were considered for scaling and for angular cosine integration was considered. So, this is possible by using Meyer wavelet decomposition for angular and scaling coefficients and discussed below and I(x, y) is converted into $\varphi_{j,k,\theta}(r,\omega)$:

$$V(\omega) = \begin{cases} 1 & |\omega| \le 1/3 \\ \cos\left[\frac{\pi}{2} v(3|\omega| - 1)\right] & 1/3 \le |\omega| \le 2/3 \\ 0 & else \end{cases} \quad (1)$$

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$$W(r) = \begin{cases} \cos\left[\frac{\pi}{2} v(5-6r)\right] & 2/3 \le r \le 5/6 \\ 1 & 5/6 \le r \le 4/3 \\ \cos[\frac{\pi}{2} v(3r-4)] & 4/3 \le r \le 5/3 \\ 0 & else \end{cases} \quad (2)$$

From eq (1) & (2) curvelet coefficient can be derived but each curvelet coefficient is comprised of three terms they are i) scaling in equation 2, ii) angle in equation 1 and iii) location is defined by 'K'.

$$K = V(\omega) * W(r) \quad (3)$$

from these three equations, our curvelet coefficient is defined as

$$\varphi_{j,k,\theta}(r,\omega) = 2^{-3j/4} * W(2^{-j}r) * V_{N_j}\left(\omega - \frac{2\pi}{k}\right) \forall\, \omega = [0,2\pi) and\ j \epsilon N \quad (4)$$

For this transform smoothness (v)is the main criteria and is observed by the following equation, it is completely dependent on polynomial equation function here in this procedure i.e, $v(x) = X^2 + 3x^3$ as an arbitrary example.

$$v(x) = \begin{cases} 0\ x \le 0 \\ 1\ x \le 1 \end{cases} x \in \mathbb{R}$$

By just using the threshold function in enhancing the edges and de-noising an image exploits the characteristics of images. So, to enhance the characteristics of an image fusion process was considered in our approach. We have different fusion approaches, such as pixel-level fusion is required to address and level coefficients of I. For this complete resolute high-frequency coefficients were only considered. Since the high-frequency components have noise and information in them. Therefore on fusing those components will elevate noise and information such that if any sharp coefficients still existed then those will gets elevated.

$$\varphi'(r,\omega) = \begin{cases} \varphi(r,\omega) + \varphi(r,\omega) & S_{\varphi}\big(\varphi(r,\omega)\big) = S\big(I(x,y)\big), \varphi(r,\omega) \ge \frac{\max(\varphi(r,\omega))}{2} \\ \varphi(r,\omega) & else \end{cases} \quad (5)$$

Here the same coefficients need to be fused since the resolution has to be matched and sharpened noise values to be raised. This fusion might be called as an equal scale with high-frequency coefficient fusion.

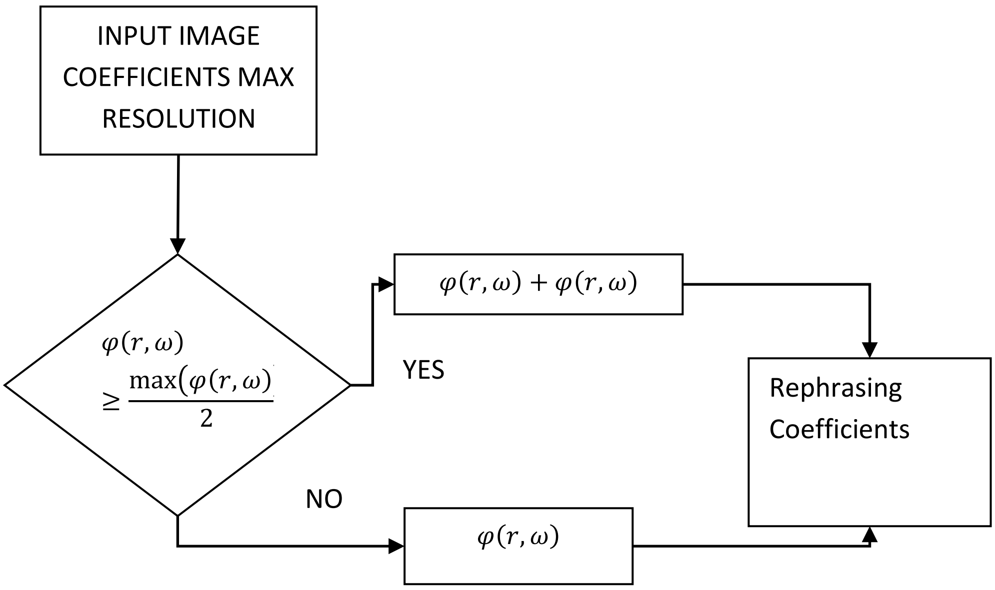

Figure 1. Fusion rule based block diagram

After the ultimate theme is reconstructed the image, but here due to high-frequency component coefficients were only considering so minimization is required for coefficients and noise needs to furthermore reduced. Therefore VMD (Variation Mode Decomposition) is applying on the fused coefficients since this all happens on the maximum resolution image of the curvelet decomposed there will be no change in lower frequency components where already pyramidal and angular filters applied. Since high-frequency components are elevated automatically the edges were enhanced and information gradually increases with a combination of smooth and less sharp values at high-frequency edges.

As the noise was observed at extreme frequency components our intrinsic mode function sets automatic threshold limits and minimizes all the low elevated components or frequencies. This automatically suppresses the noise in the high-frequency edge elevated components and helps images in efficient reconstruction. The working procedure represented mathematically in the below statements.

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In this approach Sparsity driven by VMD, Variation mode decomposition signals under different modes or intrinsic mode capacities utilizing analytics of variety. Every mode of the signal will be expected, need conservative recurrence backing around a vital frequency. VMD will figure out vital frequencies and inalienable mode works focused ahead of the individuals. Frequencies simultaneously utilizing a streamlining technique called (Alternate heading system for Multipliers) ADMM. That first detailing of the streamlining issue may be constant in time Web-domain. That compelled detailing is provided for as, [3]

$$\frac{\sum_k \|u_k^{n+1} - u_k^n\|_2^2}{\|u_k^n\|_2^2} < \epsilon \; \forall \; \omega \geq 0 \qquad (6)$$

Algorithm 1 Sparsity diverse Based on Intrinsic mode function under Variation mode decomposition Minimization

Input: Image φ, max-iteration←5

Initialization:

For n =1 to max-Iteration

Weight = $\varphi + \frac{(max(\varphi)+\min(\varphi))}{2}$

Update φ

Output: result image

For all the iterations based on the image frequency terms, our image is clustered into 3 clusters. For each cluster outcome we reconstructed the image and finds the performance parameters (MSE-Mean Square Error, PSNR- Peak Signal Noise Ratio) compared with the IMF overall reconstructed image of high frequencies and resolute curvelet coefficients then the coefficient modification was done. Then the image is reconstructed with inverse transform. The resultant values were provided by the below graph.

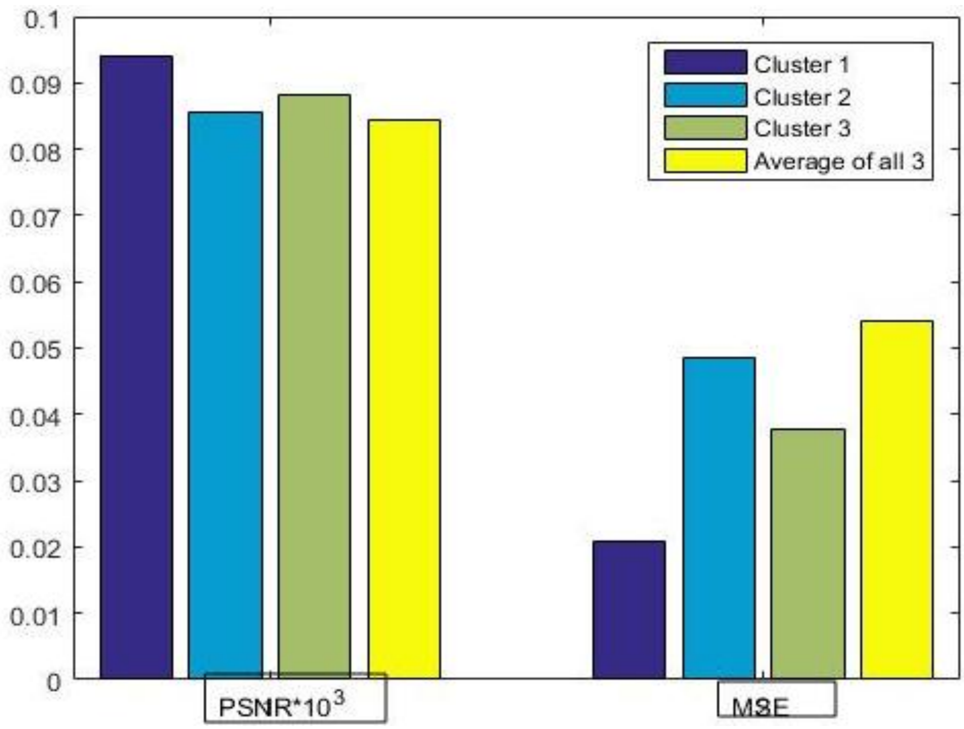


Figure 2. Performance parameters comparison between clusters and average reconstructed image.

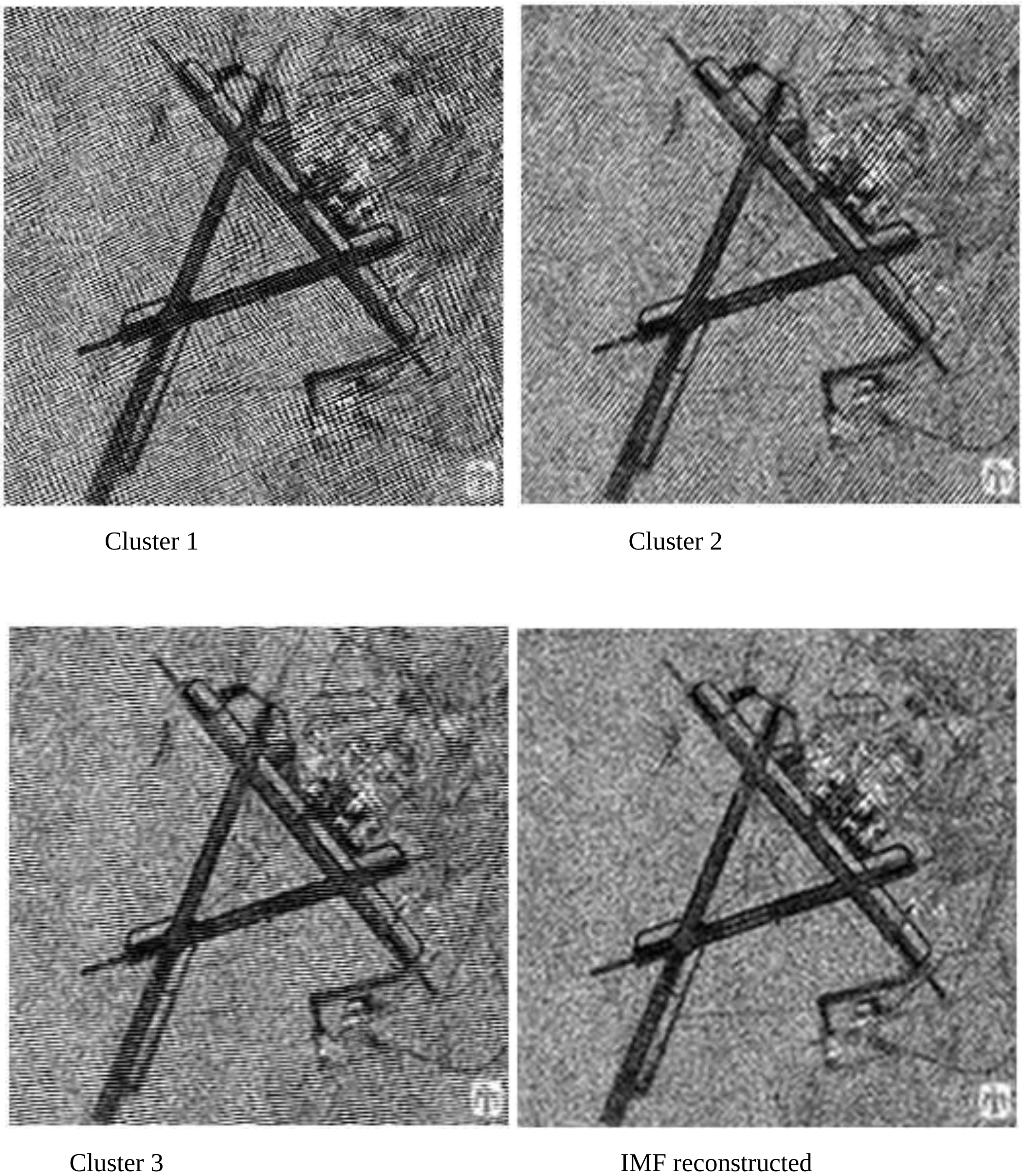
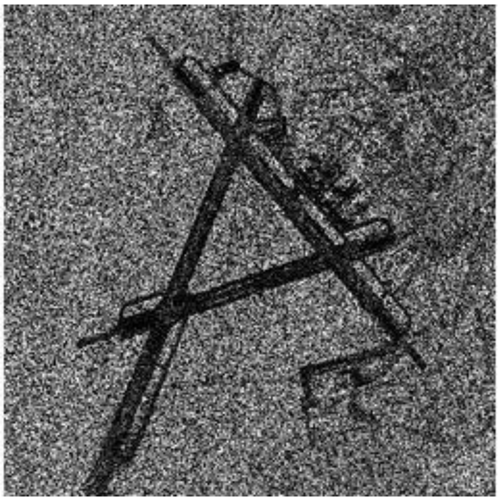


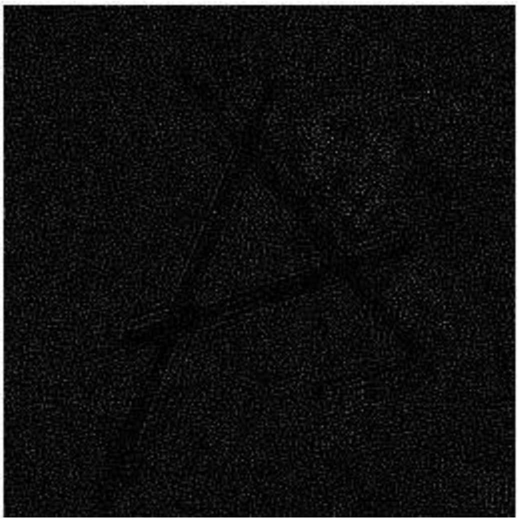
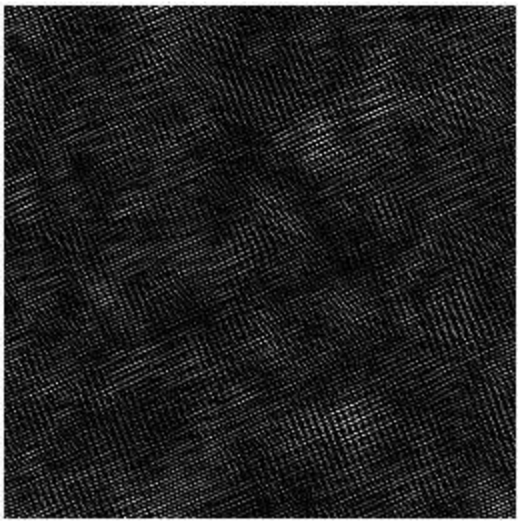
Figure 3. After inverse curvelet transform with IMF for all 3 clusters and average weight of the cluster

RESULTS

The results were identified on various SAR images for referring we displaying the results of china lake and performance graphs plotted against different variances.




Noisy Image Original Image

Fused High-Frequency coefficients Sparse Drive VMD image

Reconstructed Image with minimized noise

Figure 4. Step by Step procedure outcome for proposing approach

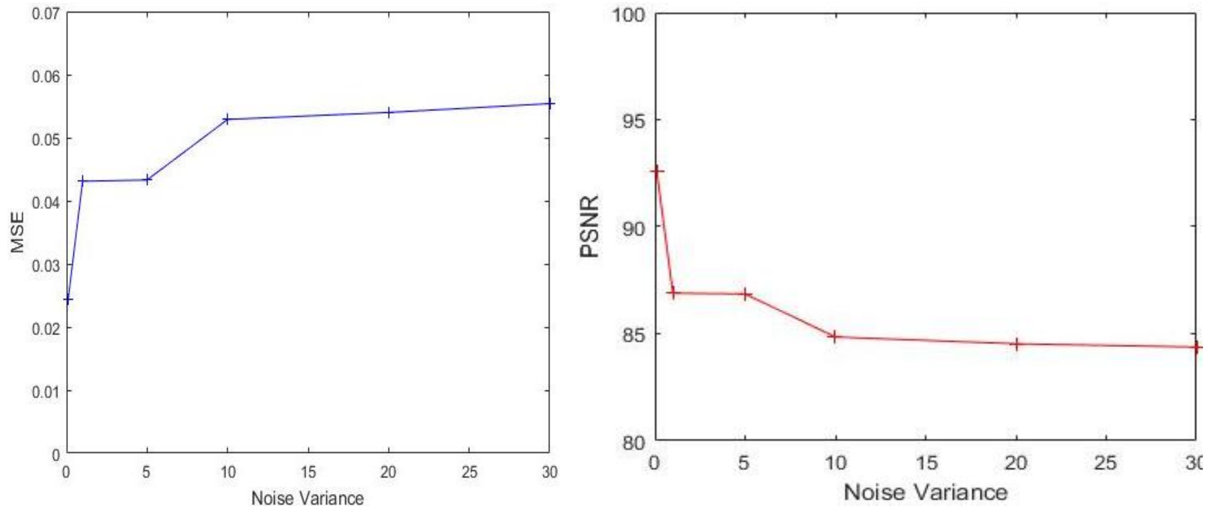


Figure 5. Performance parameters against Noise Variance

CONCLUSION

Noise minimization is the zone of area in our search. Many filtration approaches, transformations and even classifiers were use to minimize the error but were not reach the standards minimizing variance effect, in our approach of modifying the curvelet coefficients will yield the best outcome in minimizing the noise therefore a weighing iterative approach was developed for modifying the co-efficient such that image will be enhanced in contrast and due to smoothing based on weight error minimization takes place. From results we observe that varying high noise generates least change of effect in PSNR. This helps us proving that our novel approach has a capability of small effect with high range noise variances.

REFERENCES

[1] L. Xu, J. Li, Y. Shu and J. Peng, "SAR Image Denoising via Clustering-Based Principal Component Analysis," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 11, pp. 6858-6869, Nov. 2014.

[2] G. Di Martino, A. Di Simone, A. Iodice and D. Riccio, "Scattering-Based Nonlocal Means SAR Despeckling," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 6, pp. 3574-3588, June 2016.

[3] L. Gomez, C. G. Munteanu, M. E. Buemi, J. C. Jacobo-Berlles and M. E. Mejail, "Supervised Constrained Optimization of Bayesian Nonlocal Means Filter With Sigma Preselection for Despeckling SAR Images," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 51, no. 8, pp. 4563-4575, Aug. 2013.

[4] Y. Zheng, X. Zhang, B. Hou and G. Liu, "Using Combined Difference Image and K -Means Clustering for SAR Image Change Detection," in *IEEE Geoscience and Remote Sensing Letters*, vol. 11, no. 3, pp. 691-695, March 2014.

[5] O. Yousif and Y. Ban, "Improving Urban Change Detection From Multitemporal SAR Images Using PCA-NLM," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 51, no. 4, pp. 2032-2041, April 2013.

[6] C. A. Deledalle, L. Denis, F. Tupin, A. Reigber and M. Jäger, "NL-SAR: A Unified Nonlocal Framework for Resolution-Preserving (Pol)(In)SAR Denoising," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 53, no. 4, pp. 2021-2038, April 2015.

[7] C. A. Deledalle, L. Denis, G. Poggi, F. Tupin and L. Verdoliva, "Exploiting Patch Similarity for SAR Image Processing: The nonlocal paradigm," in *IEEE Signal Processing Magazine*, vol. 31, no. 4, pp. 69-78, July 2014.

[8] H. M. Zhu, W. Q. Zhong and L. C. Jiao, "Combination of Target Detection and Block-matching 3D Filter for Despeckling SAR Images," in *Electronics Letters*, vol. 49, no. 7, pp. 495-497, March 28, 2013.

[9] M. Schmitt, J. L. Schönberger and U. Stilla, "Adaptive Covariance Matrix Estimation for Multi-Baseline InSAR Data Stacks," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 11, pp. 6807-6817, Nov. 2014.

[10] W. Feng and H. Lei, "SAR Image Despeckling Using Data-Driven Tight Frame," in *IEEE Geoscience and Remote Sensing Letters*, vol. 11, no. 9, pp. 1455-1459, Sept. 2014.

[11] F. Li, L. Xu, A. Wong and D. A. Clausi, "QMCTLS: Quasi-Monte Carlo Texture Likelihood Sampling for

Despeckling of Complex Polarimetric SAR Images," in *IEEE Geoscience and Remote Sensing Letters*, vol. 12, no. 7, pp. 1566-1570, July 2015.

[12] M. Schmitt and U. Stilla, "Adaptive Multi-locking of Airborne Single-Pass Multi-Baseline InSAR Stacks," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 1, pp. 305-312, Jan. 2014.

[13] L. H. Nguyen and T. D. Tran, "Efficient and Robust RFI Extraction Via Sparse Recovery," in *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 9, no. 6, pp. 2104-2117, June 2016.

[14] Y. V. Shkvarko, J. I. Yañez, J. A. Amao and G. D. Martín del Campo, "Radar/SAR Image Resolution Enhancement via Unifying Descriptive Experiment Design Regularization and Wavelet-Domain Processing," in *IEEE Geoscience and Remote Sensing Letters*, vol. 13, no. 2, pp. 152-156, Feb. 2016.

[15] Devi Deval, S. S. KUMAR, Christy Jojy, "Comprehensive Survey on SAR Image De-Speckling Techniques", in Indian Journal of Science and Technology, 10.17485/ijst/2015/v8i24/82651, Volume 8, Issue 24, 2015.