 ISSN: 2454-4248
42 – 48

Denoising of Locally Received NOAA images for Remote Sensing Applications

K. Sateesh Kumar[1]
Research Scholar, Department of ECE
Sri Venkateswara University College of Engineering
S V University
Tirupati, AP, India
sateeshkumarkanagala@gmail.com

Dr. G. Sreenivasulu[2]
Professor, Department of ECE
Sri Venkateswara University College of Engineering
S V University
Tirupati, AP, India
gunaptieee@rediffmail.com

Abstract—Remote Sensing means capturing images of earth's surface using satellites. Remote Sensing finds its applications in agriculture sector, climate studies, forest fire detection, pollution monitoring and oceanography etc. In this paper, NOAA images are considered as Remote Sensing images. NOAA images are directly received by using L Band antenna, located at Sri Venkateswara University, Tirupati, Andhra Pradesh state, India. The received NOAA images are denoised using spatial and frequency domain denoising techniques with modified soft thresholding. The proposed thresholding technique preserves the green content of the image even after denoising by which accuracy of outcome can be increased in remote sensing applications. Comparison of the performance is done to prove that the proposed techniques are better than existing methods.

Keywords- *Denoising; NOAA ;Remote Sensing; Satellite; Thresholding*

*****

I. Introduction

Remote Sensing means capturing images of the earth's surface using satellites. In general, the received satellite images suffer with geometric and/or radiometric errors [1]. For remote sensing applications, these corrections are to be rectified to exactly overlap with the real time location of the study area. Then it is possible to map the required locations in the imagery [2]. In real time, the sources of noise in remote sensing are the image capturing sensors, the transmission path and the receiver located at the surface of the earth [3], [4]. Noise can affect the outcome in a serious manner. So, this imagery can be used for denoising stage to reduce or minimize the effect of noise on images. Noise affects the outcome from image. Hence, there is vast need to minimize the effect of noise to get best outcome [5]. The estimation of the noise content present in the images is required to apply the suitable denoising method. In this paper, preprocessing and noise estimation is done using existing methods [6]. Then, the noise estimated images are subjected to denoising section. The denoising techniques are classified into three categories based on the domain of operation, they are 1. Spatial domain 2. Frequency domain and 3. Hybrid domain. In the spatial domain denoising techniques, the correlation of pixels is considered for the denoising process [7], whereas in frequency domain based technique the denoising is done in frequency domain [8]. The hybrid denoising technique is combination of both spatial and frequency domain based denoising techniques. In this paper, denoising techniques are proposed for remote sensing applications. So, the proposed techniques considered the content of green in the images, which is the basic for remote sensing applications. The existing denoising techniques using Discrete Wavelet Transform (DWT), Dual Tree Complex Wavelet Transform with soft and hard thresholding techniques (DT-CWT-HT and DT-CWT-ST) the threshold was set by using statistical values of the image [9], [10]. As the existing techniques doesn't deal with the amount of green content in the images these denoising are not suitable for applications in remote sensing. To overcome the problem, this paper proposed denoising techniques both in spatial and frequency domains with modified soft threshold techniques (MST) for directly received NOAA images. The denoised satellite images are used to estimate the remote sensing parameters. These derived parameters are used for crop yield estimation after denoising. So, the vegetation (green content) in the imagery is more important. In remotely sensed satellite data, the content is varying with respect to season. The vegetation content of the scene in the starting period of Kharif or Rabi season is entirely different from that of at the end of season. It is due to the change in maturity of the vegetation content with season [11]. During mature period of Kharif and Rabi seasons the vegetation content is high, then the reflectance values from near infrared is high and visible bands is low so more green content appears in the image [12]. During summer the vegetation is mainly due to forest and from summer crops which is very limited in the study area. Now, the denoising technique has to accept these situations and work well. These parameters are combined with the meteorological parameters to estimate crop yield on a seasonal basis for the specific crops in the study region- Chittoor district. This section presents the selected literature review in this area of research problem. In the spatial domain denoising, [7] presented a Laplacian filter based denoising technique in spatial domain of operation for removal of impulsive noise like adaptive median filter. This technique elevated the edge features than conventional median filtering. Even though it was adaptive in nature it couldn't preserve the texture details of the image. The Inter Quartile Range (IQR) approximation technique [13] was proposed and described to denoise salt and pepper noise in real time with the help of lower order statistics (first quartile, Q1 and third inter quartile, Q3) to eliminate this problem. Due to abrupt variation in the spread of the pixel values this method was not suitable for multi resolution Remote Sensing images. In transform domain based denoising, [8] demonstrated the application of wavelets in the area of denoising by modifying the wavelet coefficients using soft thresholding technique. In this soft thresholding technique, the optimum threshold value (λ_t) was based on the variance value by minimizing the error function. For remote sensing images, this distribution of error function was different from conventional image because remote sensing images were captured in low light conditions and from large distance from the earth. The Dual-Tree Complex Wavelet Transform [10] as an extension for basic DWT. Due to the complex nature of coefficients there was a provision for the

ISSN: 2454-4248
42 – 48

exact reconstruction of the denoised image. The applications of DTCWT [9] in the area of denoising and also compared the performance of the DTCWT with DWT and reduced DWT. In the remote sensing field, [14] proposed the concept of Maximum Value Composition and estimated the canopy reflectance and vegetation dynamics for NOAA images. crop yield estimation models [15], [16] proposed using remote sensing images by implementing time series averaging technique to minimize affect of noise. From this brief literature review, the application of wavelets in the denoising of satellite images was considerable but this work was not sufficient to deal remote sensing images for applications of remote sensing. These methods were not considered the distribution of green content on images for the optimum selection of threshold which is varying on seasonal basis. In this paper, extended the work by involving the green content parameter in the selection of the threshold and to estimate the remote sensing parameters as applications of remote sensing. Unfortunately, the applications of remote sensing are more often discussed by Geologists and Agrocrats rather than Engineering researchers. This forms a considerable gap in the application of present denoising techniques in the field of remote sensing specific to applications. This paper is to fill the gap by combining Engineering concepts with remote sensing techniques to solve the problem in remote sensing application.

II. PROPOSED DENOISING TECHNIQUES

A. Spatial domain

In fact, the main problem in image denoising technique is to find out the noisy pixel in an image [17]. This problem is minimized in the proposed technique of denoising by making the threshold as adaptive in nature. In this proposed technique, the threshold is varies based on the spread of the values with the image, named as Adaptive Inter Quartile Range Approximation (AIQR). Hence, it is more suitable for real time satellite imagery in which the intensity values vary drastically with in small spatial window. The flowchart for the proposed spatial denoising technique is represented in figure 1.

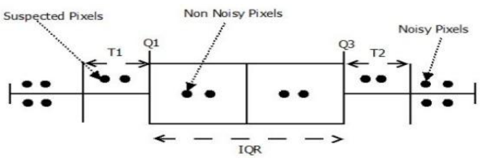


Figure 1. Schematic of IQR approach [13]

Arrange the pixels in increasing order starts from minimum to maximum through first quartile (Q1), median (M), and third quartile (Q3). IQR is defined as the difference of third quartile and first quartile. Classify the pixels into three categories like image, suspected and noisy. The existing IQR technique eliminated the outer 10-25% pixels beyond upper quartile and below the lower quartile respectively. It preserves the remaining 50% pixels. This results a huge loss in RS images. To reduce this loss as well noise the limits for threshold are defined in equations (1) and (2) and (3).

The Proposed technique of threshold is $f(Q_1, Q_3)$

$$Lower\ limit = (Q_1 - K_1) \tag{1}$$

$$Upper\ limit = (Q_3 + K_2) \tag{2}$$

where,

$$K_1 = \left(Q_1 - \sqrt{IQR}\right)\ and\ K_2 = \left(Q_3 / \sqrt{(Q_1 + Q_3)}\right) \tag{3}$$

Flowchart of the proposed AIQR is technique is represented in figure 2. In the proposed technique the threshold is selected based on the spatial variances expressed in equations (1), (2) and (3). For the noisy pixels, approximate them with the proposed technique of approximation technique which is shown in figure 3.

Therefore, the procedure of local averaging could be risky because of occurrence of another noisy pixel in the specified window, which results wrong approximation. As an example, if the value of B is 0, then the approximation is as (84+0+85+87+86)/5 = 52 which is very far from the nearest neighbors. So, by neglecting B and calculating the summation for all the surrounding pixels without B as (84+85+87+86)/4 =86. The proposed AIQR spatial domain denoising technique is implemented on NOAA images and results are discussed in the next session by comparing with the existing spatial domain denoising techniques. The problem with this proposed spatial domain denoising technique is that it eliminates some of the valid pixels which are just below the threshold in addition to the noisy pixels of the image which in turns resulting data loss. It will affect the accuracy of the outcome in remote sensing applications. The proposed threshold is depended on the spatial values of the image is limited to low noise levels. For better denoising performance, shifted to frequency domain denoising technique in which the denoising can be obtained by processing frequency content rather than direct pixels.

B. Frequency domain

Wavelets are used to analyze the frequency content of the image by dividing the image into four frequency bands LL, LH, HL and HH. DTCWT is preferred for image denoising to get better approximation of complex coefficients with shift invariance with soft thresholding. The problem with existing DTCWT-ST technique is that the threshold was chosen based on statistical values of the image. It doesn't consider the value of vegetation while applying threshold. This type of approach is not suggestible for remote sensing applications where the change is not linear and varies with time [18]. So, there is a loss of the valuable vegetation content which affects the crop yield estimation. To preserve the vegetation content, it is necessary to modify the threshold by considering it. The vegetation varies with respect to season like kharif and rabi. In order to balance both seasonal changes in real time the threshold is proposed based on the variation in the green content. Hence, a DTCWT modified soft threshold technique (DTCWT-MST) is proposed in this paper to preserve the green content in the remotely sensed satellite images by considering band reflectance values too. The figure 5 shows the flow chart of the proposed denoising technique for NOAA data. In remote sensing, band reflectance is the parameter to identify the object on the earth surface [19]. Each object on the surface reflects in different way. This value of this reflection helps to get the canopy structure and health status of the plant [20] which is considered in the proposed threshold. For NOAA data, the Normalized Difference of Vegetation Index (NDVI) is the parameter that derived from band reflectance values [20].

ISSN: 2454-4248
42 – 48

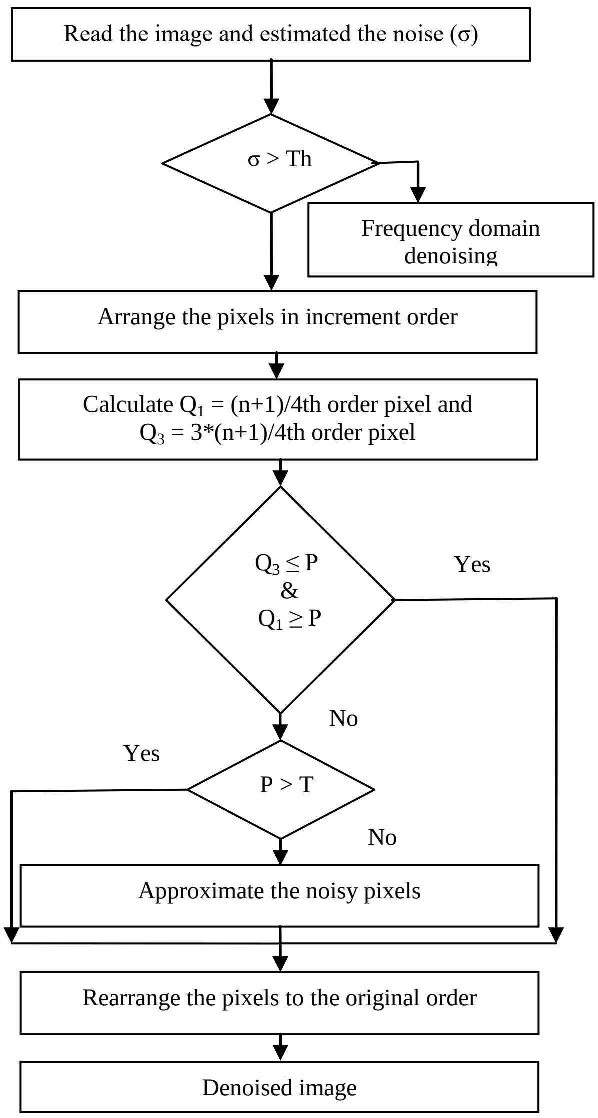


Figure 2. Flow chart of the proposed spatial domain based denoising

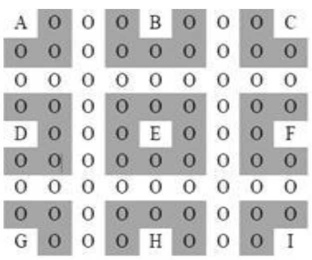


Figure 3. Approximation technique in AIQR

In the proposed thresholding technique in addition to NDVI the slope between visible and thermal bands is also considered. The modified soft threshold is proposed in this research work, expressed in equation (4).

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \tag{4}$$

Where, ρ_{NIR} and ρ_{RED} are the reflectance values of NIR and Red bands respectively.

Threshold (λ_t) = K * Slope between Visible and Thermal bands * NDVI. (5)

84	A	86
B	85	87
84	84	86

Figure 4. Condition of more than one noisy pixel

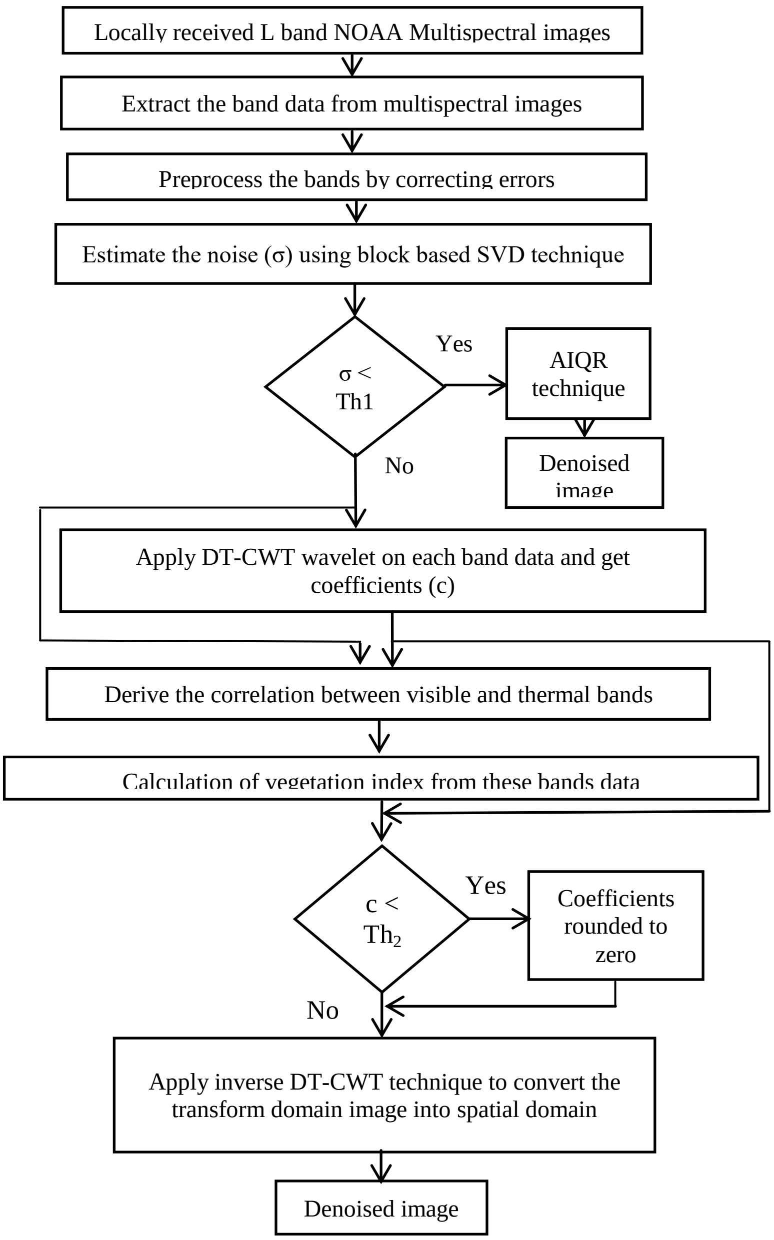


Figure 5. Flow chart of the proposed denoising technique for NOAA data

In the satellite images, due to the variation in the calibration level of the sensors, the range of captured reflectance values for visible and thermal bands are different. The reflectance values for thermal bands are called as brightness temperature [21]. The calibrated reflectance of thermal band is less compared to visible band. In order to nullify this variation, normalization is done for both thermal and visible band reflectance values to compare them. After the normalization process, the correlation between visible and thermal bands is found. The reflection from the object for the specific bands (spectral windows) is predetermined. The reflectance of water is at minimum in visible bands (band 1) and at maximum in thermal (band 4) channels, which are captured during night time. This response is same and unique for each object in the scene [1]. So for noise less data, there must be linear correlation (- 45°) between band reflectance values. Due to the impact of noise these reflectance values are changed. It disturbs the basic relation among the bands [22]. This effect is uniform in case of AWGN but not for other types of noise. So, due to noise in the band data, the slope is changing with respect to variance of the noise. To draw this inference, about 180 images of NOAA satellite (by covering all seasons) are observed and tested in different noisy conditions.

The slope values for the noise free and noisy bands are illustrated in the figures 6 and 7 respectively. In the figure 6 the band correlation is linear for noise free data and in the figure 7 the correlation is not exactly 45°. Vegetation index is the parameter which is calculated from the reflectance values of visible and thermal/infrared bands data. This value represents the green content in NOAA image. For the NOAA data its value is around 0.8 during mature period of crop and nearer to 0 (0.001) during plantation state. This value is considered to calculate the threshold for deciding whether the data is noisy or not.

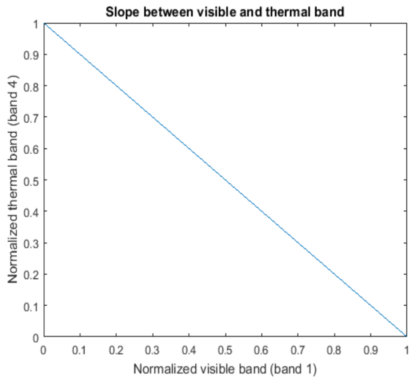


Figure 6. Slope between bands for noise free image

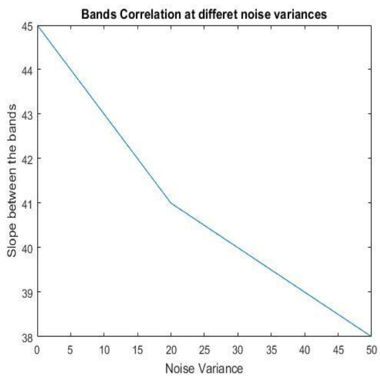
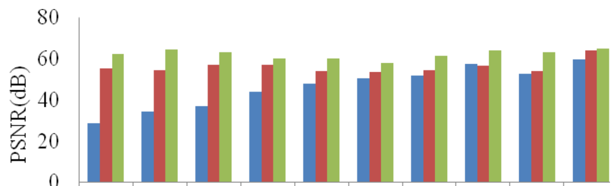


Figure 7. Slope between bands at noisy image

III. RESULTS AND DISCUSSIONS

The NOAA images used for processing are acquired by using L band receiver which is installed at Sri Venkateswara University, Tirupati. This receiver can receive the NOAA images of study region on daily basis and about 180 cloud free images which are suitable for processing are taken over a period between June 2014 and January 2017. The proposed techniques are applied on noise less images and validate the outcomes. The noise less test images is collected from National Remote Sensing Centre (NRSC), Hyderabad. In this paper, the proposed spatial domain denoising technique is compared with existing median filtering, fixed IQR techniques. These techniques are applied on a set of 10 NOAA satellite images which are shown in figure 9. (shown in next page)

The figure 8 represents the comparison of performance (in terms of Peak Signal to Noise Ratio, PSNR) of the proposed spatial domain denoising technique with existing denoising techniques. From the figure 9 it is clear that the performance of the proposed AIQR is far better than the existing spatial domain denoising techniques. The proposed frequency domain denoising technique is compared with existing DWT, DTCWT-HT, DTCWT- ST and the proposed DTCWT-MST denoising technique. These techniques are also applied on a set of 10 NOAA satellite images shown in figure 8.The figure 10 represents the comparison of performance (in terms of PSNR) of the proposed frequency domain denoising technique with existing denoising techniques. The proposed techniques are applied on noise less images and validate the outcomes.



	1	2	3	4	5	6	7	8	9	10
Median filter	28.35	34.04	36.91	43.91	47.66	50.24	51.94	57.56	52.43	59.5
Fixed IQR	55.02	54.37	57	56.98	54.04	53.66	54.28	56.37	54	63.9
Adaptive IQR	62.27	64.55	63.05	60.23	59.95	57.98	61.18	64.19	63.01	65

Figure 8. Comparison of performance for spatial domain denoising techniques for NOAA images

From the figure 10 it is clear that the performance of the proposed DTCWT-MST is far better than the existing frequency domain denoising techniques. The comparison of the proposed spatial domain denoising technique (AIQR) is compared with the proposed frequency domain denoising technique (DTCWT-MST) in terms of PSNR is shown in figure 11. From figure 11 the performance of proposed frequency domain denoising technique is better than the proposed spatial domain denoising technique.

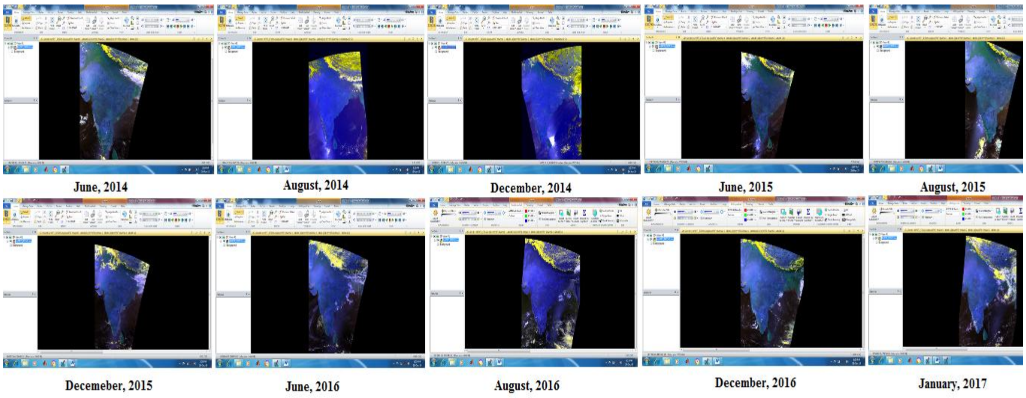
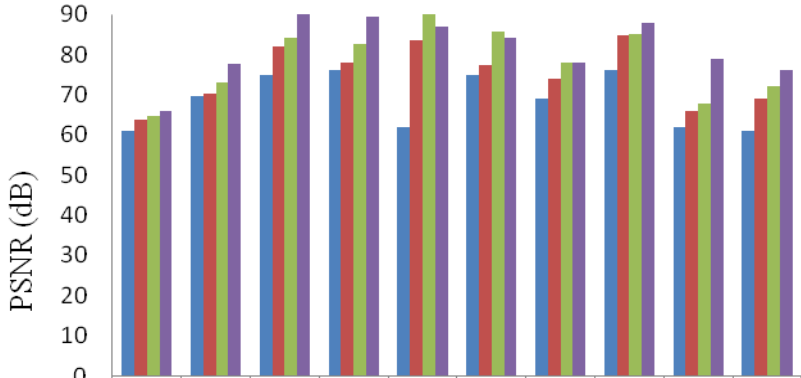
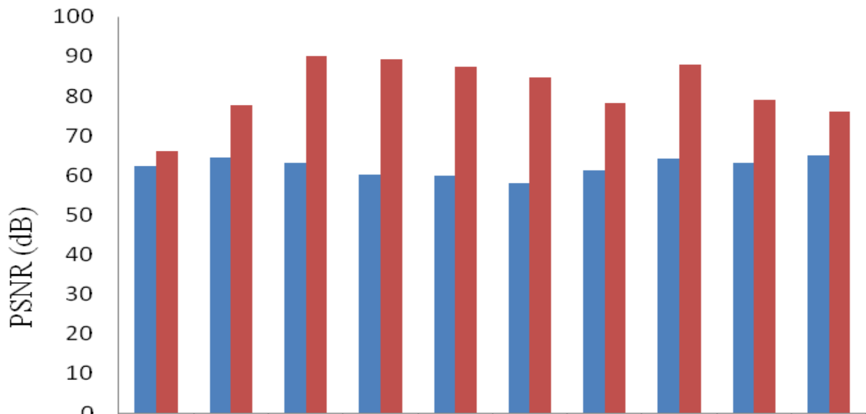


Figure 9. Dataset of NOAA images



	1	2	3	4	5	6	7	8	9	10
DWT (Existing)	61.1	69.6	75	76.2	62	75	69	76	62	61
DTCWT-HT (Existing)	63.7	70.4	82.1	78.1	83.7	77.4	73.9	84.7	66	69
DTCWT-ST (Existing)	64.76	72.93	84.14	82.68	89.96	85.63	77.9	85.12	67.87	72.19
Proposed (DTCWT-MST)	65.99	77.6	89.97	89.33	87.05	84.18	78.12	87.87	78.99	76.12

Figure 10. Comparison of performance (PSNR) of frequency domain denoising techniques for NOAA images



	1	2	3	4	5	6	7	8	9	10
AIQR	62.27	64.55	63.05	60.23	59.95	57.98	61.18	64.19	63.01	65.12
DTCWT-MS	65.99	77.6	89.97	89.33	87.42	84.68	78.12	87.87	78.99	76.12

Figure 11. Comparison of PSNR (dB) for the proposed denoising techniques for NOAA images

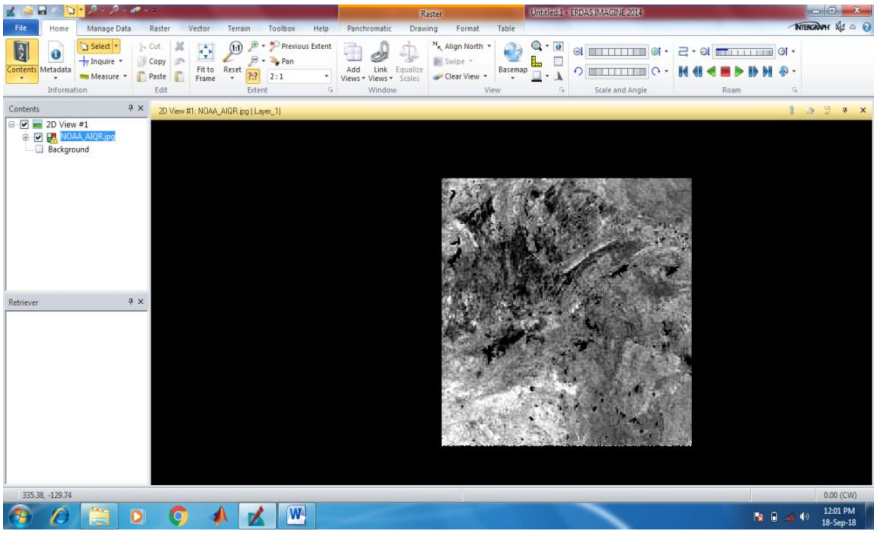


Figure 12. Denoised NOAA image using proposed AIQR denoising technique

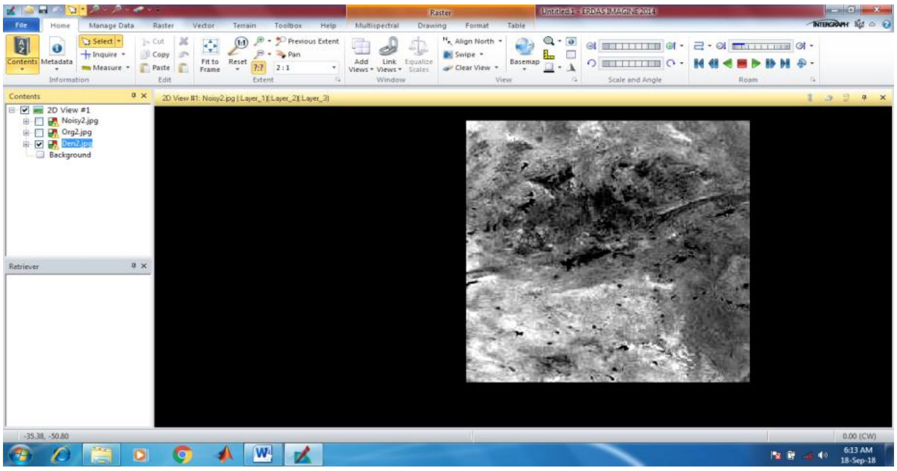


Figure 13. Denoised NOAA image using proposed AIQR denoising technique

IV. CONCLUSION

From this research work, it can be concluded that the complexity wise AIQR based denoising is better choice in spatial domain for low level of noise. If the estimated noise variance is between 5 and 10. Where as if the estimated noise variance is between 20 and 50, the frequency domain denoising technique, DTCWT-MST denoising technique is preferred. The proposed frequency domain denoising technique is far better in performance (in terms of PSNR) then the existing techniques. Further when compared, the performance of the proposed frequency domain denoising technique is better than the proposed spatial domain denoising technique due to consideration of green content in the selection of threshold for NOAA images. As a future work this can be extended to other high resolution satellite images like Landsat 8 and Indian Remote Sensing satellite (IRS).

REFERENCES

[1] George Joseph, "Fundamentals of Remote Sensing", Second edition, Universities Press, 2005.

[2] Arms ton J.D, Danaher, T.J, et al., "Geometric Correction of Landsat MSS,TM and ETM+ Imagery for Mapping of Woody Vegetation Cover and Change Detection in Queensland", Climate Impacts and Natural Resource Systems, 2002.

[3] Salem S. A, Kalyankar N. V, and Khamithar S. D, "A Comparative Study of Removal Noise from Remote Sensing Image", International Journal of Computer Science Issues, vol. 7, no. 1, Jan 2010, pp.32-36

[4] Pawan P, Sumit S, Manoj G, and Ashok K N," Image De-noising by Various Filters for Different Noise", International Journal of Computer Applications, Vol. 9, no. 4, Nov 2010, 0975 – 8887

[5] Liu, P., Huang, F., Li, G., and Liu, Z, "Remote Sensing Image Denoising Using Partial Differential Equations and Auxiliary Images as Priors", IEEE Geoscience and Remote Sensing Letters, vol. 9, no. 3, 2012, pp.358–362

[6] B. R Corner, R. M Narayanan, and S.E. Reichenbach, "Noise Estimation in Remote Sensing Imagery Using Data Masking", International Journal of Remote Sensning, 2003,24:689-702.

[7] Wei Liu and Weisi Lin, "Gaussian Noise Level Estimation in SVD Domain for Images", IEEE International Conference on Multimedia and Expo, 2012.

[8] G. Hanji and M. V. Latte, "A New Impulse Noise Detection and Filtering Algorithm", International Journal of Scientific Research and Publications, Vol. 2, Issue 1, 2012.

[9] Firas Aji lJassim, “Image Denoising using Interquartile Range Filter with Local Averaging”, International Journal of Soft Computing and Engineering, Volume-2, Issue-6, January 2013.

[10] Savita Gupta and Lakhwinderkaur, “Image Denoising using Wavelet Thresholding”, Conference Proceedings of ICVGIP-Dec 2002.

[11] Thomas G. V. Niel, and Tim R. Mc Vicar, “Determining Temporal Windows for Crop Discrimination with Remote Sensing: A Case Study in South Eastern Australia”, Computers and Electronics in Agriculture, 2004, pp. 91-108.

[12] A R S Marcal, and G G Wright, “The Use of NOAA-AVHRR NDVI Maximum Value Composites for Scotland and Initial Comparisons With The Land Cover Census on a Scottish Regional and District Basis”, International Journal of Remote Sensing, vol. 18, no. 3, 1997, 491-503.

[13] Firas Ajil Jassim, “Image Denoising using Interquartile Range Filter with Local Averaging”, International Journal of Soft Computing and Engineering, Volume-2, Issue-6, January 2013.

[14] Holben N. B, “Characteristics of Maximum Value Composite Images from Temporal AVHRR Data”, International Journal of Remote Sensing, 2007, pp. 1417-1434.

[15] L Vijayan, “Significance of Meteorological Parameters in the Implementation of Agriculture Engineering Practices in and around Tabuk Region, KSA”, International Journal of Applied Science and Technology, vol. 3, no.5, 2013.

[16] Huang J et al, “Analysis of NDVI Data for Crop Yield Identification”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing , vol. 7, issue 11, 2014.

[17] Chen, Guangyong, Fengyuan Zhu, and Pheng Ann Heng, “An Efficient Statistical Method for Image Noise Level Estimation”, IEEE International Conference on Computer Vision, 2015.

[18] Ansari R H, and Mohan B K, “Noise Filtering of Remotely Sensed Images using Iterative Thresholding of Wavelet and Curvelet Transforms”, The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. XL-1, 2014 pp-57-64.

[19] Waldo K, Jan C. O., Konrad J. W., et al.,“Improving Land Cover Class Separation Using An Extended Kalman Filter On MODIS NDVI Time-Series Data”, IEEE Geo Science and Remote Sensing Letters, vol. 7, no. 2, April 2010.

[20] Sergil S, Nataliia K., et. al., “Efficiency Assessment of Multi Temporal C-Band Radarsat-2 Intensity and Landsat 8 Surface Reflectance Satellite Imagery for Crop Classification in Ukraine”, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2015.

[21] H. Hu, F. Chen and Q. Wang, "Estimating the Effective Wavelength of The Thermal Band for Accurate Brightness Temperature Retrieval: Methods and Comparison", Proceedings 2011 IEEE International Conference on Spatial Data Mining and Geographical Knowledge Services, 2011,pp. 330-334.

[22] Jinru X, and Baofeng, “Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications”, Journal of Sensors, 2017.