International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-5 Issue-1, October 2015

Multiresolution Color Denoising using Biorthogonal Wavelets for Satellite Images

Malini S, Lizy Abraham, R.S. Moni

Abstract*— Satellite images are required to be of high quality since most of the databases created by different countries are using the images especially for Geographical Information System (GIS) applications and military purposes. Recently available high resolution multi spectral imaging sensors facilitate greatly the process of feature extraction which is given as the input to the database systems. But because of the sensor vibrations, different angle of inclinations, influence of clouds & shadows and many unwanted factors create noise in satellite images which ultimately affects the quality of feature extraction process. In this paper a novel method of multiresolution colour image denoising using bi-orthogonal wavelets is discussed. The method is compared with other orthogonal wavelet denoising schemes and existing techniques based on patch processing. Experimental analysis and visual inspection of images validates the superior performance of the proposed method.

***Index Terms*— Multispectral, Biorthogonal, Daubechies, Decomposition, Multispec32, Quality Measures**

I. INTRODUCTION

Image denoising is an important image processing task, both as a process itself, and as a component in other processes. Very many ways to denoise an image or a set of data exists. In earlier methods of image denoising, linear models have been used. The common approaches are to use a Median filter [1, 2], Gaussian filter [3], or a 2nd order [4] or 4th order PDE [5] model. The methods are good for gray-scale images and especially being used for denoising MRI images [6]. The main property of a good image denoising model is that it will remove noise while preserving edges and important features. Over the past decades multiresolution image denoising is proposed using DCT [7] and DWT [8, 9] but still such schemes are not suitable for satellite images in which each and every pixel contain enormous information which should not be neglected like other images where we need only an overall clarity [10]. Recently many multiresolution wavelet denoising methods concentrate on satellite images. The work done by [11, 12] are providing very good results but only with satellite panchromatic images. The most effective works in this field are based on patch processing of images where patches are initially formed based on some local or nonlocal similarity pixels. BM3D method [13] and HOSVD method [14] are the well-known methods in patch based image denoising. Recent works for the denoising of satellite RGB images are by Kugu, E [15] which uses bilateral filters with improved Strength Pareto Evolutionary Algorithm (SPEA2) and by T. Sree Sharmila [16] which uses Hybrid Directional Lifting (HDL) technique for image denoising that involves pixel classification and orientation estimation. But the methods are computationally complex and computation time is enormously large. In this work, we have developed an effective method for multispectral satellite image denoising using the unique properties of biorthogonal wavelets. The method proposed in this paper is computationally efficient than the existing time consuming algorithms. Also the algorithm is edge preserving with good visual quality images. Experimental results are provided with different evaluation methods like Peak Signal to Noise Ratio (PSNR), Correlation Coefficient (CC) and Structural Similarity (SSIM) Index to validate the superior quality of our algorithm compared to orthogonal discrete wavelet transform (DWT) based methods. The rest of the paper is organized as follows: The details of multiresolution analysis using orthogonal and biorthogonal wavelets are explained in Section 2. After discussing about the proposed method in section 3, experimental results are presented in section 4. Finally, a discussion about the work is given on section 5 and the paper is concluded on section 6.

II. MULTIRESOLUTION ANALYSIS USING ORTHOGONAL AND BIORTHOGONAL WAVELETS

The orthogonal discrete wavelet transform is an implementation of the wavelet transform using discrete set of wavelet scales and translations in which the scaling functions must be orthogonal to its discrete translations. This can be realized using digital FIR filters h [k] and g [k] that define the relationship of scaling and wavelet functions and their translations. The scaling and wavelet functions can be written respectively as given in eqns. (1) and (2)

$$\emptyset(t) = \sum_{k=0}^{N-1} h(k)\sqrt{2}\,\emptyset(2t-k) \tag{1}$$

$$\psi(t) = \sum_{k=0}^{N-1} g(k)\sqrt{2}\,\emptyset(2t-k) \tag{2}$$

These FIR filters are also orthogonal. They are characterized by maximal number of vanishing moments for some given support. The wavelet function, as seen from the equation, strongly depends on scaling function. The scaling and wavelet functions must satisfy some necessary conditions such as orthogonality, smoothness, discrete decomposition, compact support and finite vanishing moments. Based on the constraints, Daubechies [17] derived equations for the filters h[k] and g[k].

Manuscript published on 30 October 2015.
* Correspondence Author (s)
Malini S*, Research Scholar, LBS Centre for Science & Technology, Trivandrum, Kerala, India.
Dr. Lizy Abraham, Assistant Professor, LBS Institute of Technology for Women, Trivandrum, Kerala, India.
Dr. R.S. Moni, Professor, Marian Engineering College, Trivandrum, Kerala, India.

Due to the stringent requirement of orthogonality and orthonormality the FIR filters used in daubechies (db_N) wavelets cannot be strictly symmetric. Hence the filters are not linear phase resulting in some visual artifacts. This can be rectified if the bases are biorthogonal [18]. i.e., when the filters are inverses but not necessarily transposes, the filter bank is said to be biorthogonal. In this case, FIR filters can be symmetrical giving rise to linear phase. Hence the processed signal has less visual artifacts. However, this result can only be realized using two scaling functions ϕ & $\bar{\phi}$ and two wavelet functions ψ & $\bar{\psi}$. When the same filters are used for decomposition and reconstruction, perfect reconstruction is incompatible with symmetry. This problem can be solved by using two filters instead of one which is the basic requirement of biorthogonal wavelets. The wavelet $\bar{\psi}$ is used for analysis and ψ is used for reconstruction. The wavelets ψ & $\bar{\psi}$ are related by duality relation (3).

$$\int \psi_{j,k}(x)\bar{\psi}_{j',k'}(x)dx = 0 \text{ for } k = k' \ \& \ j = j' \qquad (3)$$

The analysis and synthesis filters in biorthogonal wavelets are symmetric FIR filters leading to linear phase which cannot be obtained in orthogonal wavelets. Therefore, better reconstruction of the image is possible in biorthogonal wavelets.

III. METHODOLOGY

The methodology of implementation of the algorithm proposed in this paper for satellite image denoising is discussed in this section. The overall flow of the system is given in Fig.1.

A. Image Pre-processing

Multispectral high resolution satellite images have Red (R), Green (G), Blue (B) and Near Infrared (NIR) components in it. NIR band is used mostly for feature extraction applications. By discarding the NIR bands using multispec32 [19] which is a freeware multispectral image data analysis software from satellite images, RGB color images are obtained.

There exist several successful denoising algorithms for one band gray scale images. Theoretically these algorithms can be straightforwardly extended to each of the planes of RGB for denoising. However in practice, results obtained are poor unless proper color space transformation is done from RGB. Some of the common color spaces are YUV, YCbCr, YIQ, HSV etc. Each of these has one luminance component and two color components. After conducting experiments with these color spaces, it is observed that the best color space for denoising application is YUV when processing is done on all three components [20].

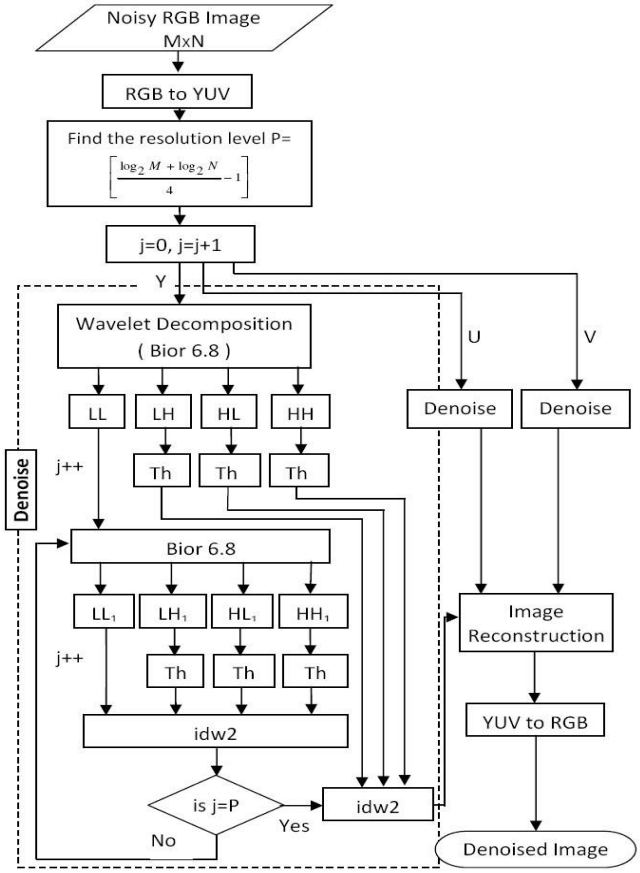
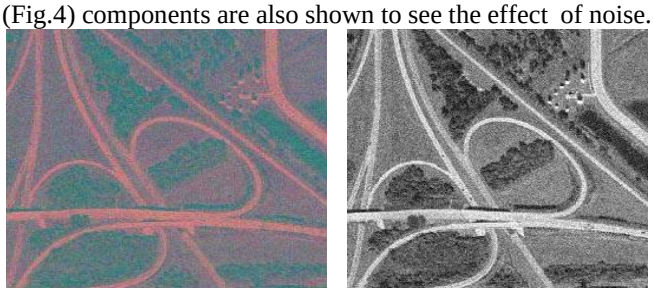


Fig.1 Overall Flow of the System

(a) **(b)**

Fig. 2 (a) RGB Satellite Image (b) RGB Satellite Image with Gaussian Noise

Fig.2(a) is an RGB satellite image obtained from Google Earth software. We have purposefully degraded the test image by adding Gaussian noise of 20% in all three components (Fig.2(b)). The corresponding YUV image is shown in Fig.3(a). The luminous (Fig.3(b)) and chrominance (Fig.4) components are also shown to see the effect of noise.



(a) **(b)**

Fig. 3 (a) YUV Image (b) Luminous Image

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

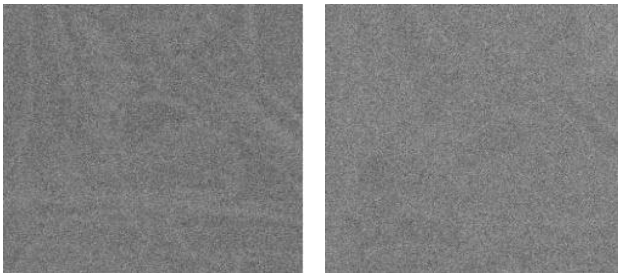


Fig. 4 Chrominance (U&V) Components

B. Wavelet Decomposition

In this work wavelet decomposition is done using biorthogonal wavelet 6.8 which has more smoothened filter coefficients for denoising the satellite images. The scaling and wavelet functions have more similarity with the orthogonal wavelet db10 [15]. Hence for comparison of the denoising performance of bior6.8, denoising using db10 is also carried out. Further, performance of wavelet analysis using Haar (db1) is done as it has unique properties of orthogonality and compact support.

The wavelet decomposition is done on all three components separately since all the channels are affected by noise. One channel of the noisy image is decomposed to four bands (LL, LH, HL, HH) at the first level. How many levels of wavelet decomposition should be done for a particular image is always a problem, but obviously number of levels depends on resolution of the image. In order to automate the problem the following algorithm is chosen for our work:

1. Choose the resolution level *P* for the wavelet decomposition of the image as $0 \le j \le \frac{\log_2 M + \log_2 N}{4} - 1$, where M x N is the spatial resolution of the image.
2. Select *Y* channel.
3. Apply series of convolutions along rows and columns of image matrix using g[k] and h[k] of the biorthogonal filter (bior 6.8) respectively.
4. Implementation proceeds with the suppression of noisy pixels from the smoothened image. The procedure is explained in *section C*.
5. If $j \neq P$, go to step 3. Else go to step 5.
6. Obtain the decomposed image at level *P*.
7. Repeat steps 3 to 6 for *U* & *V* channels.

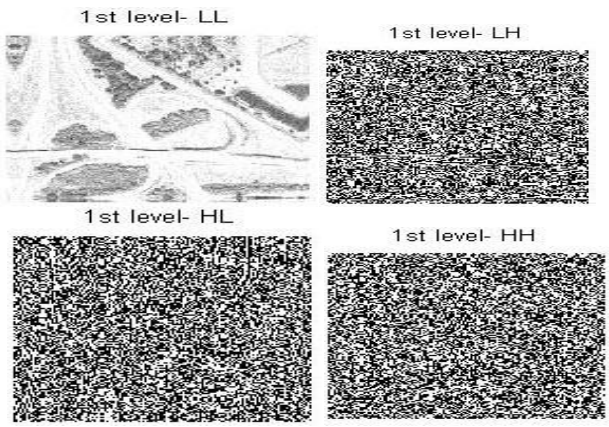


Fig. 5 First Level Decomposition Results

The noisy image shown in Fig.2 (b) has a spatial resolution of 128x128, and so the algorithm decomposes the image up to 2nd level. The figures 5 & 6 show the results of first and second levels of decomposition for Y channel.

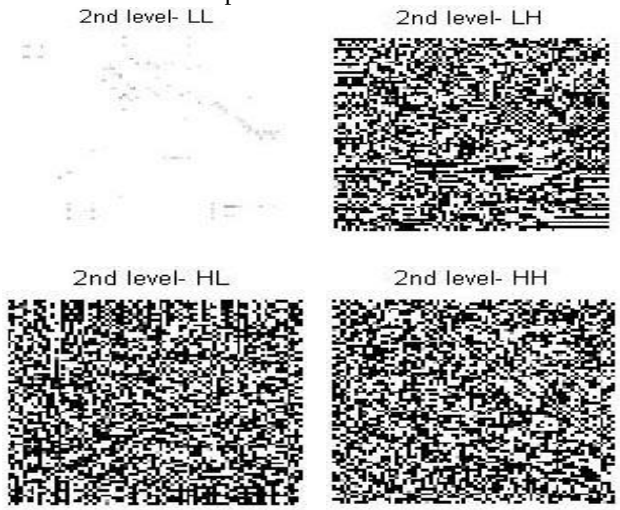


Fig. 6 Second Level Decomposition Results

C. Wavelet Denoising

The multiresolution analysis separated signal and noise components into different bands. The detailed bands LH, HL and HH which contain smaller magnitude coefficients as noise are shrunk towards zero to eliminate noise.

Here we use an adaptive soft thresholding function which has advantages of near-optimal minimax rate over a large range. The threshold varies for each band and each level automatically depending on the characteristics of the image which gives rise to good denoising performance. For the generalized guassian noise, it yields a smaller risk and it gives rise to more visually pleasant images [21]. A universal threshold estimate *T* for an image of size [M, N] and noise variance σ^2 is (eqn.4):

$$T = \sqrt{2\sigma^2 \log[3 \times (M/2) \times (N/2)]} \qquad (4)$$

The variance σ^2 of the noise is estimated on LH, HL and HH images by averaging the squares of the wavelet coefficients. After determining individual thresholds for the three detailed bands LH, HL and HH at each level, image denoising is done using soft thresholding techniques at each level. The noisy pixels are shrunk towards zero using the following equation:

$$\eta_T(x) = \mathrm{sgn}(x).\max(|x| - T, 0) \qquad (5)$$

Considering the fact that the wavelet transformed image has both positive and negative intensity values, the following algorithm is used for denoising (Table 1):

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

TABLE I : ALGORITHM FOR DENOISING

```
If [each pixel of LH image < LH threshold
   and each pixel of LH image > - (LH threshold)]
     then [apply equation (5);]
     else [ sustain the pixel value as such;]
```

The same procedure is applied for HL and HH images using HL and HH thresholds. Using another set of thresholds, the algorithm is applied to next consecutive levels and U&V channels as well. Although other shrinkage techniques like Visu shrink, SURE shrink and Baye's shrink were used for denoising, for satellite colour images results were not better than that proposed in this paper.

D. Wavelet Reconstruction

The thresholded detailed bands and the low frequency approximation bands are synthesized to get the denoised output. Reconstructed image is obtained by performing the inverse wavelet transform on the wavelet decomposed & denoised image with the help of reconstruction filters (eqn.6).

$$s(t) = \sum_{j \in J} \sum_{k \in J} C(j,k) \psi_{j,k}(x) \qquad (6)$$

where *s (t)* is the reconstructed image and *(j,k)* represent scale and position respectively. *C (j, k)* is the coefficient function and $\psi_{j,k}(x)$ is the wavelet function as used in DWT.

In the case of biorthogonal wavelets, scaling function $\bar{\psi}$ is used for analysis and ψ for reconstruction. After reconstructing the denoised Y image (Fig.7(a)), the same process is done for other two chrominance components (U & V). The denoised Y image is then concatenated with the denoised chrominance components (Fig.8), to get the YUV image (Fig.9 (a)). Finally the YUV image is converted back to RGB image to get the denoised reconstructed satellite image (Fig.9(b)). The process was repeated with db10 and Haar wavelets.

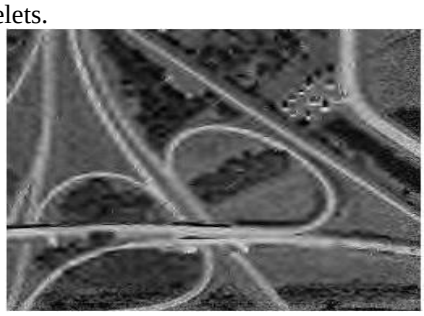


Fig. 7 Denoised Intensity Image of Fig.2 (b)

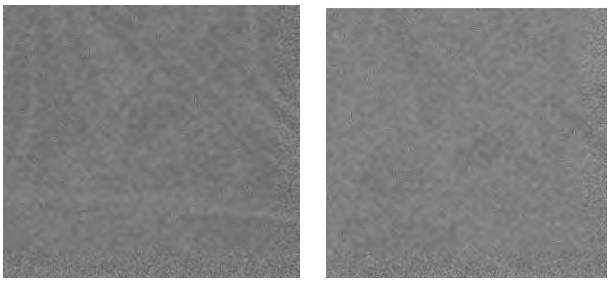
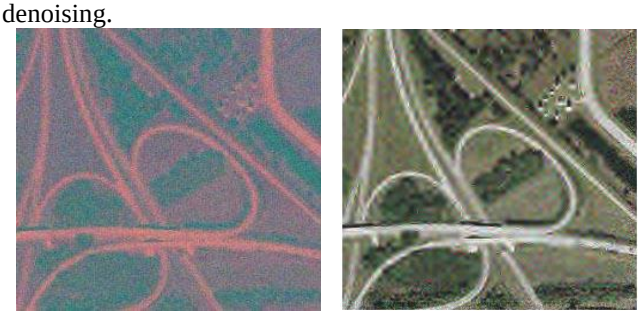


Fig. 8 Denoised Chrominance Components

IV. EXPERIMENTAL RESULTS

The proposed method of multiresolution color denoising using biorthogonal wavelets is applied among a number of satellite images of different resolutions. The same algorithm is applied using db10 and Haar wavelets to validate the superior performance of biorthogonal wavelets for image denoising.

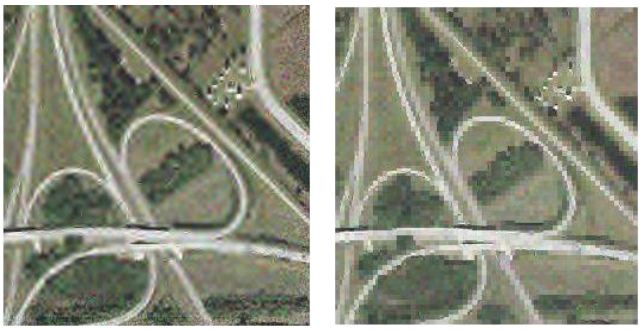


(a) (b)

Fig. 9 (a) Denoised YUV Image (b) Denoised RGB Satellite Image

Seeing the denoised images, we can understand that Haar wavelet is not much suitable for color image denoising since the scaling and wavelet functions are not smoothly truncating. Biorthogonal and db10 seems to have similar visual qualities but quantitative analysis given in table 2 shows that biorthogonal wavelet have better result compared to the other one. Fig.10 shows the result of db10 and Haar wavelet denoised images respectively for the test image given in Fig.2(b). Fig. 11(a) and Fig. 14(a) are multispectral satellite images. We have added 15% speckle and impulse noise respectively to the images. Fig. 11(a) is an IKONOS level 3A 1m resolution images of Ankara city, Turkey, acquired in year 2007.

The images are distributed by Space Imaging Middle East (SIME), Dubai, UAE (http://www.spaceimagingme.com), which is a regional affiliate of GeoEye providing high-resolution satellite imagery of Middle East region. Fig. 14(a) is IKONOS image of 1-m resolution taken on 28th August 2004, obtained from Spatial Energy, Beijing, China (http://www.spatialenergy.com).



(a) (b)

Fig.10 (a) Denoised Image using db10 (b) Denoised Image using Haar

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

(a) (b)

Fig. 11 (a) Multispectral Satellite Image (b) Multispectral Satellite Image with 15% Speckle Noise

The multispectral image is the Historic Centre of Warsaw which is the oldest historic district of Poland located on the Vistula River.

For both images, we have discarded the NIR band using multispec32 software [19]. Denoising of the images is done using the three wavelets with the proposed method. Emphasizing the results, the output images shown in Fig.12 (a) & Fig.15 (a) proves that biorthogonal wavelets are very much suitable for colour image denoising compared to db10 (Fig. 12(b) & Fig. 15(b)) and Haar wavelets (fig.13 & fig.16).

Fig.17 (a) is a noisy random satellite image degraded due to various unknown factors. Though it is a panchromatic (grey scale) satellite image, we have selected it as one of the test image since the noise included in the image is unknown. By visual inspection itself, it is noticed that the denoised image using Haar wavelet (Fig.18(b)) is somewhat comparable with the other wavelet systems (Fig.17(b) & Fig.18(a)) for this case alone since it is a grey scale image. However the quantitative parameters listed in Table II show that Haar wavelet is not so good for denoising color images.

(a) (b)

Fig.12 (a) Denoised Image using bior 6.8 (b) Denoised Image using db10

Fig.13 Denoised Image using Haar Wavelet

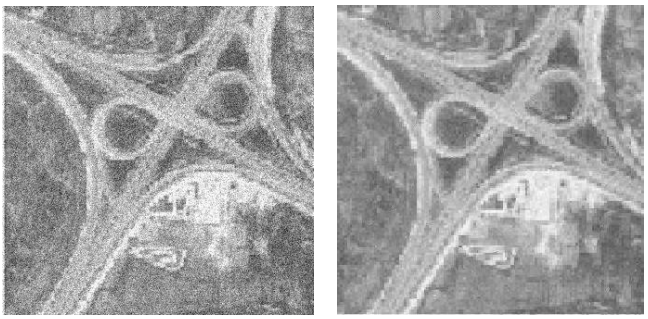
(a) (b)

Fig. 14 (a) Multispectral Satellite Image (b) Multispectral Satellite Image with 15% Impulse Noise

(a) (b)

Fig.15 (a) Denoised Image using bior 6.8 (b) Denoised Image using db10

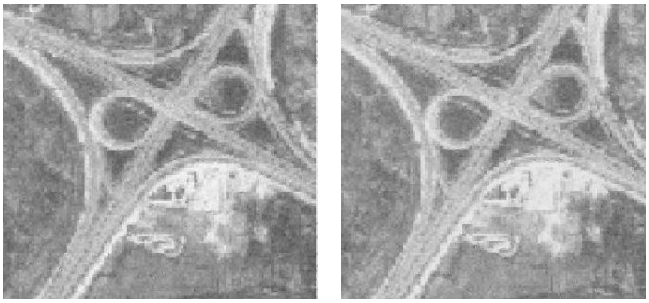
Fig.16: Denoised Image using Haar Wavelet



(a) (b)

Fig.17 (a) Degraded Panchromatic Satellite Image (b) Denoised Image using bior 6.8

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)



(a) (b)

Fig.18 (a) Denoised Image using db10 (b) Denoised Image using Haar Wavelet

For accuracy analysis and performance comparison we have used the well known quality measures used for denoised images like Peak Signal to Noise Ratio (PSNR), Correlation Coefficient (CC) and Structural Similarity (SSIM) Index [22]. The value of the above measures for the test images using all the three methods is given in table 2. It can be seen that image denoising using biorthogonal wavelet outperforms the other two wavelet denoising methods considering each of the quality measurements given in Table II.

TABLE II: ACCURACY ASSESSMENT

Image	Haar			Db10			Biorthogonal			Computation Time (sec)
	PSNR	CC	SSIM	PSNR	CC	SSIM	PSNR	CC	SSIM	
Fig.2(b)	34.78	0.61	0.68	37.05	0.77	0.72	38.14	0.86	0.79	1.57
Fig.11(b)	31.97	0.63	0.77	36.23	0.70	0.80	38.69	0.74	0.84	1.59
Fig.14(b)	29.43	0.72	0.67	34.51	0.78	0.79	34.93	0.77	0.85	1.87
Fig.17(b)	31.05	0.89	0.82	32.37	0.89	0.81	33.43	0.89	0.80	1.24

V. DISCUSSIONS

The accepted efficient denoising techniques based on patch processing [13, 14] are computationally complex and processing time is enormously large (it takes more than 10 minutes to denoise a color image of size 128x128) [14]. But the method proposed in this paper is procedurally simple and computationally efficient, taking less than 2sec (table 2) for a noisy color image of the same size. One of the important and specific aspects of processing satellite images is that visual quality of the image should be of high standard for its application of object recognition and detection. It is this aspect which is considered in the choice of methodology of denoising in this paper. Although other recently developed tools such as Curvelet and Contourlet [23] are available for image denoising, which preserves edges and curves, their standalone denoising effect is not as good as that proposed in this paper. The choice of YUV colour space with biorthogonal wavelet analysis and soft thresholding is found to give better performance of noise reduction along with better visual quality and less visual artifacts. In this work, we are using an adaptive thresholding scheme based on the statistical properties of the image. The method varies automatically for each band and each level which gives good PSNR, SSIM and CC values. As seen from the denoised reconstructed images, the method is edge preserving and results in good visual quality images. But the resultant images have a blurring effect if the image is affected with high density noise.

VI. CONCLUSION

A novel color image denoising method using biorthogonal wavelets especially meant for satellite images is proposed in this paper, consuming less time with good visual quality compared to existing effective methods based on patch processing. The method is also compared with db10 and haar wavelet systems. Experimental results prove that image denoising using biorthogonal wavelets have better performance than the orthogonal wavelet systems. Quality assessment of the method is done using various measures such as PSNR, CC and SSIM Index. The results of the quality of denoised images and quantitative analysis given in table 2, show that proposed method of denoising using biorthogonal wavelets is superior to the other two wavelet methods; namely the Haar and Db10. Future works concentrates on better thresholding methods for the images affected with high density noise.

REFERENCES

1. S. Shrestha, "Image Denoising using New Adaptive based Median Filter", An International Journal of Signal & Image Processing (SIPIJ), Vol.5, NO.4, PP. 1-13, Aug. 2014.
2. V. Govindaraj and G. Sengottaiyan, "Survey of Image Denoising using Different Filters", International Journal of Science, Engineering and Technology Research (IJSETR), Vol.2, NO. 2, pp. 344-351, Feb.2013.
3. B. K. Shreyamsha Kumar, "Image Denoising based on Gaussian/Bilateral Filter and its Method for Noise Thresholding", Signal, Image and Video Processing , Springer, vol.7, no.6, pp 1159-1172, 2012.
4. Huaibin Wang, Yuanquan Wang and Wenqi Ren, Image Denoising Using Anisotropic Second and Fourth Order Diffusions Based on Gradient Vector Convolution, ComSIS, Vol. 9, No. 4, Special Issue, pp.1493-1511, Dec.2012.
5. Seongjai Kim and Hyeona Lim, "Fourth Order Partial Differential Equations for Effective Image Denoising", Seventh Mississippi State - UAB Conference on Differential Equations and Computational SIMULATIONS, Conf. 17, PP. 107–121, 2009.
6. A. Norouzi, M. Shafry, M.Rahim, A. Altameem, T. Saba, A. Rad, A. Rehman and M. Uddin, "Medical Image Segmentation Methods, Algorithms, and Applications", IETE Journal of Technical Review, vol.31, no. 3, pp. 199-213, June 2014.
7. D. Radford,A. Kurekin, D. Marshall and K. Lever, "A New DCT-based Multiresolution Method for Simultaneous Denoising and Fusion of SAR Images," 9th International Conf. on Information Fusion,Florence, pp. 1-8, 2006.
8. S. Kother Mohideen, S. Arumuga Perumal, and M. Mohamed Sathik, "Image De-noising using Discrete Wavelet Ttransform", IJCSNS International Journal of Computer Science and Network Security, VOL.8, NO.1, pp. 213-216, Jan.2008.
9. J. N. Ellinas, T. Mandadelis, A. Tzortzis and L. Aslanoglou, "Image De-noising using Wavelets", T.E.I. of Piraeus Applied Research Review, vol. IX, no. 1, pp. 97-109, 2004.
10. L. Abraham and M. Sasikumar, "Analysis of Satellite Images for the Extraction of Structural Features", IETE Journal of Technical Review, pp. 118 – 127, vol.31, no.2, APRIL 2014.
11. M. Vijay and L. Saranya Devi, "Speckle Noise Reduction in Satellite Images Using Spatially Adaptive Wavelet Thresholding", International Journal of Computer Science and Information Technologies, Vol. 3, NO. 2, PP. 3432-3435, 2012.
12. Parthasarathy Subashini and Marimuthu Krishnaveni, "Image Denoising Based on Wavelet Analysis for Satellite Imagery, Advances in Wavelet Theory and Their Applications in Engineering, Physics and Technology, Dumitru Baleanu (Ed.), ISBN: 978-953-51-0494-0, INTECH., PP. 449-474, 2012.
13. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian, "BM3D Image denoising by 3D transform-domain collaborative Filtering", IEEE Trans. Image Processing, vol. 16, no. 8, pp.2080-2095, Aug. 2007.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

14. Rajwade, A. Rangarajan and A. Banerjee., "Image Denoising Using the Higher Order Singular Value Decomposition", IEEE Trans. Pattern Analysis and Machine Intel., vol.35 , no.4, pp.849 – 862, April 2013.
15. Kugu, E. , "Satellite Image Denoising using Bilateral Filter with SPEA2 Optimized Parameters", 6th International Conference on Recent Advances in Space Technologies (RAST), pp. 217 – 223, 2013.
16. T. Sree Sharmila, K. Ramar, "Efficient Analysis of Hybrid Directional Lifting Technique for Satellite Image Denoising", Signal, Image and Video Processing , Springer, vol. 8, no. 7, pp. 1399-1404, Aug.2012.
17. I. Daubechies, "Ten Lectures on Wavelets", CBMS, SIAM, 61, 1994.
18. S.V.Narasimham, Nandini Bazumallick & S. Veena, "Introduction to Wavelet Transform: A Signal Processing Approach", Naroza Publishing House, New Delhi, 2011.
19. http://cobweb.ecn.purdue.edu/~biehl/MultiSpec
20. Nai-Xiang Lian, Zagorodnov, V., Yap-Peng Tan, "Color Image Denoising using Wavelets and Minimum Cut Analysis", IEEE Signal Processing Letters, vol.12 , no.11 , pp.741 – 744, Nov. 2005.
21. Chang, S.G.,Bin Yu, Vetterli, M., "Adaptive Wavelet Thresholding for Image Denoising and Compression", IEEE Trans.Image Processing, vol.9 , no.9, pp.1532 – 1546, Sept. 2000.
22. Z. Wang, A. C., Bovik, H. R., Sheikh & E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity", IEEE Transactions on Image Processing, vol. 13, no. 4, pp. 600-612, Apr. 2004.
23. Janwei Ma & Gerlind Plonka, "The Curvelet Transform", IEEE Signal Processing Magazine, pp.118-133, March 2010.

Malini S is pursuing PhD in image denoising, and is presently working as a Research Scholar, LBS Centre for Science & Technology, Trivandrum, Kerala, India. She had completed her B-Tech in Electronics & Communication Engineering from Kerala University and M.E from Anna University. She has worked as a Lecturer in Marian Engineering, College, Kazhakuttom, Trivandrum and T.John Engineering College, Bangalore. Her research works include various image denoising schemes using Image-Signal processing tools. She has presented and published several papers in this subject in international conferences and journals.

Dr. Lizy Abraham completed her PhD in satellite images, and is presently working as an Assistant Professor, LBS Institute of Technology for Women, Trivandrum, Kerala, India. Her research works include extraction of structural features such as roads, buildings and bridges from satellite images using Image-Signal processing tools and soft computing methods. She has presented and published several papers in this subject in international conferences and journals. She has also published a book in this area, and another book on LabVIEW for signal processing and control system applications. She is currently doing a research project on 'Monitoring & Analysis of Simulated Spacecraft Parameters using Lab VIEW' in which various parameters are acquired from different sensors.

.

Dr. R.S. Moni is presently working as a Professor in Marian Engineering College, Trivandrum, Kerala, India. He received his BSc (Engg) degree from College of Engineering, Trivandrum, India. His M-Tech degree and Ph.D are from Indian Institute of Technology, Madras, India. He has over 40 years of teaching experience in various engineering colleges as Professor and Principal and also is a former Director of Technical Education. His research interests are in image and signal processing, and the application of artificial intelligence tools for pattern recognition tasks. He has published more than 50 papers in this field in various international journals.

.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)