Hybrid Algorithms Based on Transforms for Denoising Satellite Images

L.Ramamurthy, S.Vardarajan

Abstract— ***The image acquired from a sensor is always degraded by some form of noise. The noise can be estimated and removed by the process of denoising. Recently, the use of Hybrid Algorithms for denoising have gained popularity. The most commonly used transformation are Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). DCT has the property of more energy compaction and requires less resources for computational whereas DWT is a multiresolution transformation. The proposed Hybrid Algorithms take advantage of both of the algorithms and this reduces the false contouring and blocking articrafts effectively. In this paper, the Hybrid Algorithms are evaluated for various images by comparing in terms of Mean Square Error, Peak Signal to Noise Ratio, Coefficient of Variance, Structural Similarity Index and Mean Structural Similarity Index.***

Index Terms— ***CV, Denoising, MSE, PSNR, SSIM, MSSIM***

1. INTRODUCTION

The noise free images are required for processing in satellite applications. MPEG-4[1]-[2] is the next generation visual coding standards that provides great flexibility for evaluating visual objects in multimedia based applications and improve the visual quality at very low bit rate. The arbitrarily shaped visual object must preserve its shape and texture. The existing methods include rectangle shape images and videos and coding like DCT coding and DWT coding. In conventional methods, the bounding box straighten the arbitrarily images, the values are padded in the pixel position outside the object and the pixels inside the object are coded and padded in the bounding box together, which might be inefficient [3]-[7].

The problem of removing the noise of visual objects without decomposing its attributes such as edges, textures, colors, contrast, etc., had been researched for the last two decades and many other types of denoising techniques have been developed.

The total variance based noise removing method developed by Rudin et al.[25] had much influence in image community and inspire a large quantity of formulations for removing the noise of an image. In [8] - [10] the Non-Local Means (NLM) algorithm manages to correctly remove most of the noises, they tend to not properly recover some of the image details. These methods also primarily deal with additive Gaussian noise, whereas for many images the noise model is unknown; in such cases, there is still ample room for improvement [10], [11],[12], [13].

This paper evaluates the Hybrid Algorithms as applied to denoise various satellite images. Section II deals about the Existing Transforms used for denoising the images. In Section III, Hybrid Algorithms designed for reducing articrafts are described. Section IV reports the result of the various algorithms and comparisons with other coding techniques for different images. Section V will conclude the paper.

II. EXISTING TRANSFORMS FOR DENOISING

(a) Discrete Cosine Transform (DCT)

A DCT indicates the data points of input as a sum of cosine functions with various oscillating frequency and amplitude. The two main types of discrete cosine transform schemes are: one dimensional discrete cosine transform and two dimensional discrete cosine transform. Since an image is transformed as two 2-D matrix, two dimensional DCT is used. The two dimensional discrete cosine transform for a size of x input sequence can be described as [14] [15]:

$$D_{DCT}(i,j) = \frac{1}{\sqrt{2N}} B(i)\,B(j) \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} M(x,y)\cos\left[\frac{2x+1}{2N} i\pi\right]\cos\left[\frac{2x+1}{2N} j\pi\right]$$

Where,

$$B(u) = \begin{cases} \frac{1}{2} & if\ \ u = 0 \\ 1 & if\ \ u > 0 \end{cases}$$

x × y is the size of the input data M(x, y).

In DCT, all the informations were accommodating in a small number at low frequency coefficients which are easily affected by noise. The low frequency coefficients are called as DC components and remaining coefficients are said to be AC components. Using 8 × 8 quantization table, the DCT coefficients are quantized as in the JPGE standard. The equation for two dimensional inverse DCT transform is given below.

$$D_{IDCT}(i,j) = \frac{1}{\sqrt{2N}} \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} B(i)B(j)\,Ddequant(i,j)\cos\left[\frac{2x+1}{2N} i\pi\right]\cos\left[\frac{2x+1}{2N} j\pi\right]$$

Where,

$$B(u) = \begin{cases} \frac{1}{2} & if\ \ u = 0 \\ 1 & if\ \ u > 0 \end{cases}$$

Revised Version Manuscript Received on 30 May, 2018.

L.Ramamurthy, Reaserch Scholar, Department of Electronics and Communication Engineering, Rayalaseema University, Kurnool, Andhra Pradesh, India

Dr. S.Vardarajan, Professor, Department of Electronics & Communication Engineering, Sri Venkateswara University College of Engineering, Tirupati, A.P, India

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

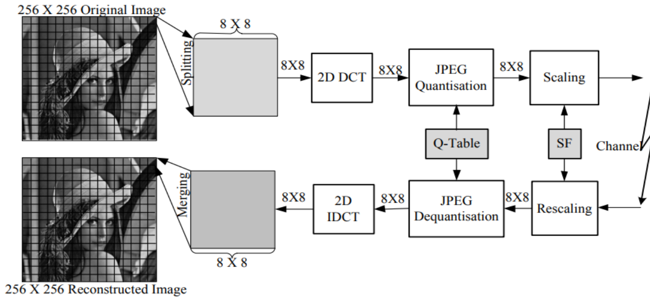

fig. 1: Block Diagram of 2D-DCT

There exist certain limitations of DCT like blocking articrafts and False Contouring. The distortion like blocking articrafts occurs due to high compression rate and looks abnormally as large pixel blocks. The false contouring is due to smoothly graded area of visual objects was distorted and appears as a contour map for some image[17]-[22]. The heavy quantization of the transform coefficients is the main reason for false contouring effect.

(b) Discrete Wavelet Transform (DWT)

The DWT indicate the visual information as the sum of wavelet function, also called as wavelet with various location and scale [8]. It represents the data as a set of high pass (detail) and low pass (approximate) coefficients. The input data is transferred through set of low pass and high pass filters. Filter kernel for this work is[■ (1&1@1&-1)]. The output of high pass and low pass filters are down sampled by 2. This process is one dimensional DWT and the schematic is given in figure 2.

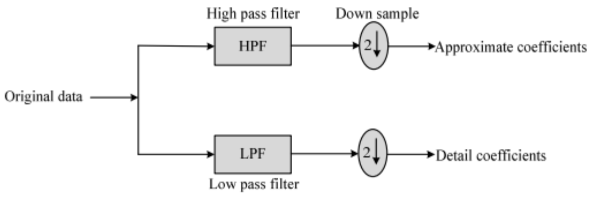

Figure.2: Schematic of 1D forward DWT

In two dimensional DWT, the input data was sent through low pass filter and high pass filter in two different directions in both row and column. The outputs are then down sampled by 2 in each direction. The complete process is depicted in figure 3. The output is then obtained as four coefficients LL, HL, LH and HH. The first alphabet is the transformation in row and the second alphabet is the transformation in column. The alphabet L represent low pass signal and H indicates high pass signal. LH signal represents a low pass signal in row and HH represents a high pass in column. LH signal consist of horizontal elements, HL and HH consist of vertical and diagonal elements respectively.

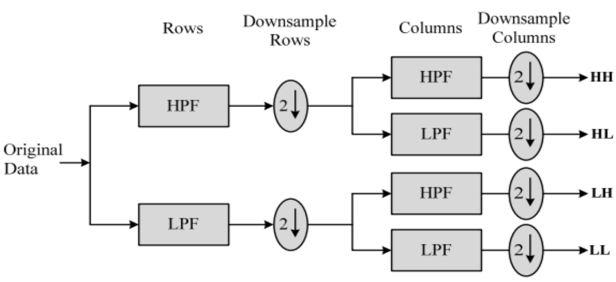

Figure.3: Schematic representation of 2D forward DWT

As shown in Figure 4, during DWT reconstruction, input data can be obtained by decomposing LL coefficient for different levels in multiple resolutions [38]. The compressed data is up sampled by a factor of 2 in order to reconstruct the output data. Then the signal was sent through the same set of high pass and low pass filters in both row and column. The complete reconstruction process was given in figure 5.

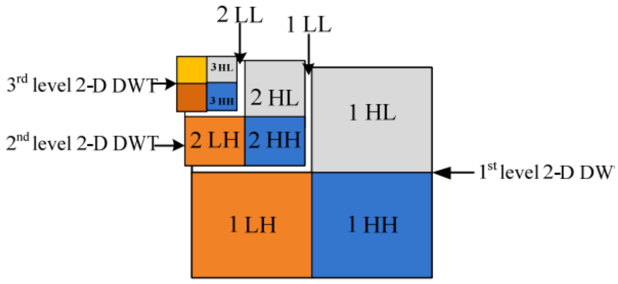

Figure.4: Multilevel Forward DWT

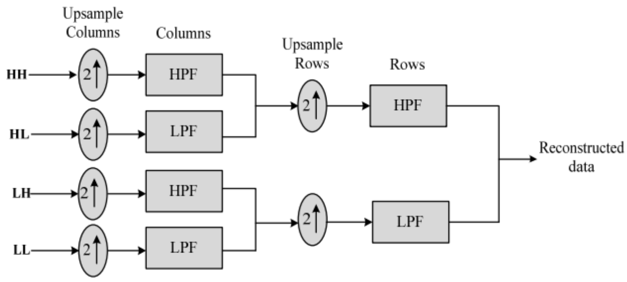

Figure.5: Schematic representation of 2D Inverse DWT

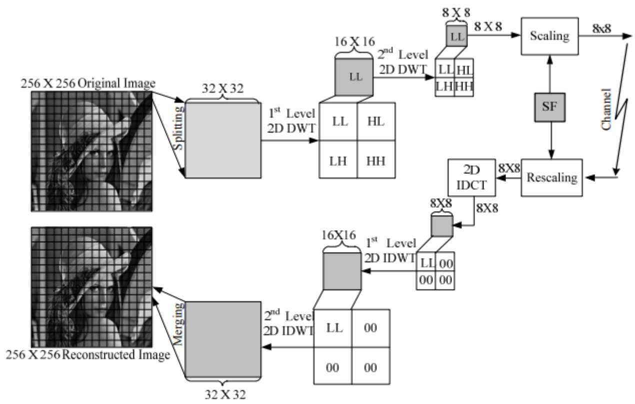

Figure.6: Schematic representation of DWT Decomposition

The process goes on for one more level. The coefficients are split up by a constant scaling factor to obtain the desired compression ratio. At last for reconstructing the data, the data was rescaled, padded with zeros and directed to the wavelet filters. Figure 6 shows the conplete procedure of 2-D DWT compression and reconstruction.

III. PROPOSED HYBRID ALGORITHMS

The Discrete Cosine Transform and Discrete Wavelet Transform are used for denoising of images. DCT had more energy compaction property with less resources for computational, while DWT is multi resolution transformation.

The proposed Hybrid Algorithms take advantage of both of the algorithms and thus reduce the false contouring and blocking articrafts effectively.

The algorithms are developed in such a way that the subsamples are processed in DCT while the main block is processed by DWT in Hybrid DWT-DCT as shown in figure 7.

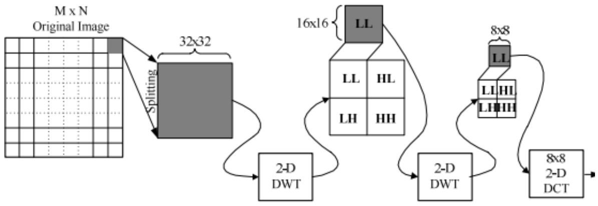

Fig.7: representation of Hybrid DWT-DCT Algorithm

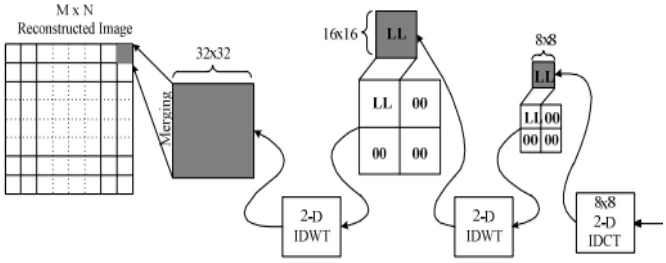

Fig.8: Schematic representation of Inverse Hybrid DWT-DCT Algorithm

Algorithm for Hybrid DWT-DCT:

The sub sampling strategies based on DCT and DWT algorithms, discussed above, the Hybrid algorithms for a satellite image can be described as follows.

1) Read the input raw satellite vision data
2) Estimate the noise in the image.
3) Apply the 2-D DWT with proper sub sampling strategy.
4) choose the wavelet coefficients that are to be processed to perform 2-D DWT and obtain the second level low pass wavelet coefficients.
5) Perform the 2-D DCT the obtained low pass coefficients.
6) Now perform 2-D Inverse DCT and subsequently two times 2-D Inverse DWT for reconstruction of denoised image.

Similarly, the subsamples are processed in DWT while the main block is processed by DCT in Hybrid DCT-DWT as shown in figure 9 and figure10.

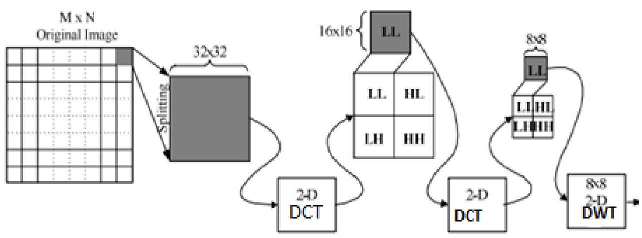

Figure.9: Diagrammatic representation of Hybrid DWT-DCT Algorithm

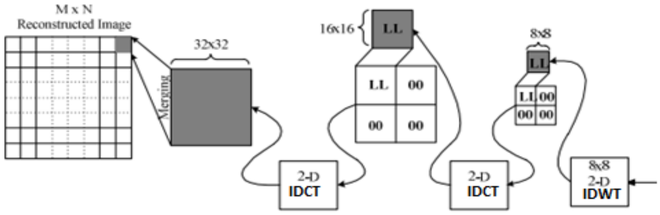

Fig.10: Schematic diagram of Inverse Hybrid DWT-DCT Algorithm

IV. RESULTS AND DISCUSSION

The Algorithms are coded and evaluated in MATLAB. The images considered for performance evaluation are shown in figures 11, 12, 13, 14 and 15. The Performance of hybrid algorithms is compared with existing algorithms based on MSE, PSNR, CV, SSIM and MSSIM parameters.

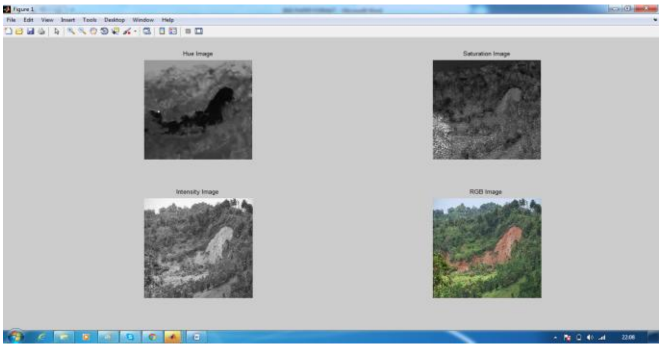

Figure11: Input Image - 1

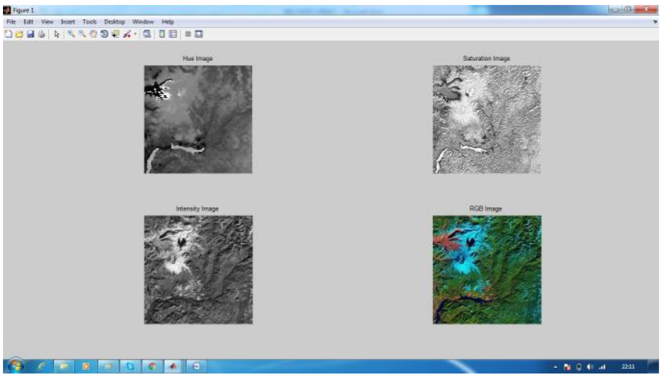

Figure12: Input Image - 2

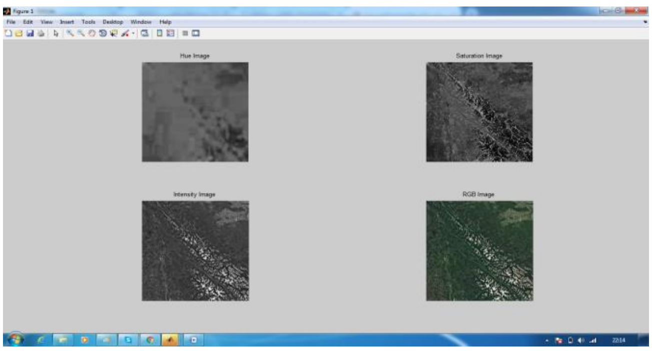

Figure13: Input Image - 3

*Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication*

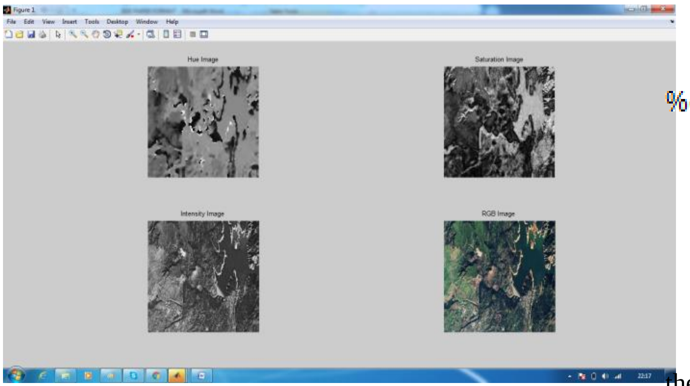

Figure14: Input Image - 4

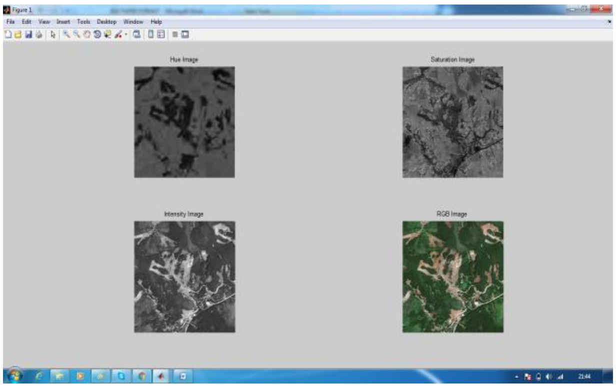

Figure15: Input Image - 5

The corresponding noise estimates are calculated for each channel as shown in figure 16, which shows that there exists noise in the images.

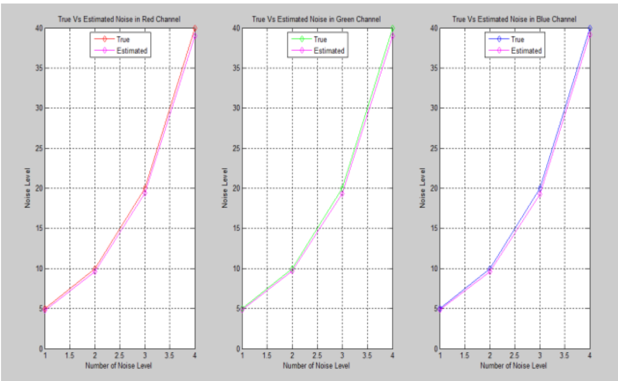

Fig.16: Noise Estimate for Test Images

The ratio of the maximum signal power to the power of distorted noise that affects the quality is the peak signal to noise ratio.

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

where MSE is mean square error and said to be the average squared difference between the estimated values and estimated or the average of square of errors and is given by

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

The PSNR must be as high as possible. The mean square error must be as low as possible.

The coefficient of variance is a measure of relative variability between the images, given by

$$\%CV = \frac{100\sqrt{\frac{\in X^2 - \frac{(\in X)^2}{N}}{N-1}}}{\bar{X}}$$

%CV= percent coefficient of variation

$\in X$ = sum of the assay values

N= number of assay values

$\in X^2$ = sum of squares of all the values

$(\in X)^2$= square of the sum of all assay values

$\bar{X}$=arithmetic average of all assay values

The lower the value of the coefficient of variation the more the precise estimate

The method of estimating the similarity between two images was regarded as a Structural Similarity index. The SSIM index is also defined as a measure of quality of the visual object being compared by considering the quality of other visual data as perfect and is given by

$$S(x,y) = f(l(x,y), c(x,y), s(x,y))$$

$$SSIM(x,y) = [l(x,y)]^{\alpha}.[c(x,y)]^{\beta}.[s(x,y)]^{\gamma}$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

Comparison of structure s(x, y) was performed on the normalized signals $(x- \mu_x)/\sigma_x$ and $(y- \mu_y)/\sigma_y$.

where the variables α, β and γ are used to vary the relative importance of the three components.

The mean structural similarity for quantitative analysis of super-resolution image based on the size of the window which is given by

$$MSSIM(X,Y) = \frac{1}{M}\sum_{j=1}^{M} SSIM(x_j, y_j)$$

The processed and reconstructed images for Hybrid DWT-DCT are shown in figure 17.

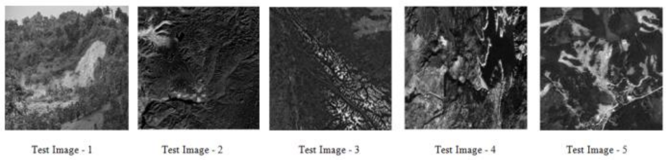

Fig.17: Reconstructed Images of Hybrid DWT-DCT Algorithm

The Table 1 shows the various parameters used for comparing the denoising algorithms. From the table, it was clear that among all the algorithms Hybrid DWT-DCT algorithm has the best possible characteristics.

Table 1: Comparison of Denoising Algorithms based on various parameters

Method/ Images	Test Image – 1				
	MSE	PSNR	CV	SSIM	MSSIM
DCT	4.6175e+03	11.4867	45.8474	4.0682e-04	-5.1406e-04
DWT	751.0471	28.2299	47.0400	0.3054	0.1627
DWT-DCT	506.3219	29.8954	45.6364	0.9988	0.3229
DCT-DWT	5.1052e+03	25.8299	60.9139	0.4682	-0.0015
	Test Image – 2				
DCT	3.7023e+03	12.4461	76.9491	2.6988e-04	7.9426e-04
DWT	1.9393e+03	27.3432	76.5332	0.2397	0.1347
DWT-DCT	569.2167	29.6713	68.9416	0.9994	0.3385

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

DCT-DWT	2.9860e+03	26.7816	69.5503	0.2397	0.0988
	Test Image – 3				
DCT	2.8372e+03	13.6018	54.7035	0.0047	0.0062
DWT	788.5256	28.4754	49.1566	0.4241	0.2892
DWT-DCT	483.0586	31.9986	47.3910	0.9990	0.5239
DCT-DWT	798.7914	28.1722	51.0053	0.4241	0.2882
	Test Image – 4				
DCT	3.7059e+03	12.4418	69.7524	0.0074	0.0042
DWT	1.0954e+03	28.2315	57.8401	0.3804	0.2050
DWT-DCT	630.0937	30.6140	53.0960	0.9987	0.4252
DCT-DWT	1.2833e+03	27.0931	67.0268	0.3804	0.2025
	Test Image - 5				
DCT	250.7565	24.1383	62.9258	0.6489	0.9334
DWT	748.4971	28.4657	60.5928	0.4329	0.2543
DWT-DCT	383.4546	31.8982	54.2012	0.9986	0.4629
DCT-DWT	839.7779	28.7878	61.2381	0.4329	0.2489

Figure 18 shows the maximum peak signal to noise ratio for Hybrid DWT-DCT Algorithm.

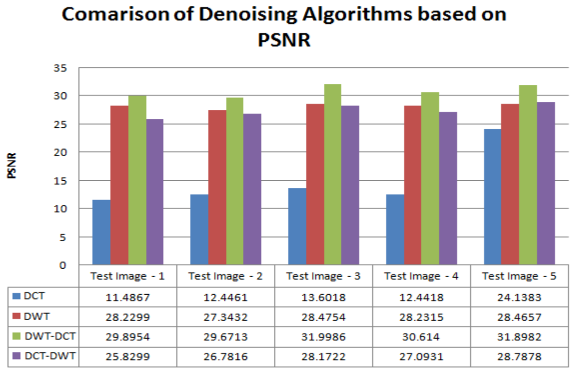

Fig.18: Comparison of Denoising Algorithms based on PSNR

Figure 19 shows that the coefficient of variance is minimum for Hybrid DWT-DCT Algorithm.

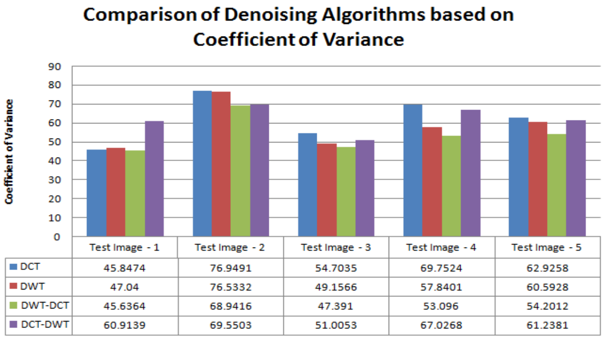

Fig.19: Comparision of Denoising Algorithms based on Coefficient of Variance

Figure 20 shows that the Structural Similarity Index is maximum for Hybrid DWT-DCT Algorithm.

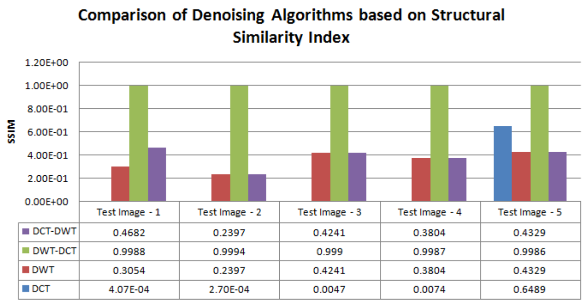

Fig.20: Comparision of Denoising Algorithms based on Structural Similarity Index

V. CONCLUSION

This paper presents description of Hybrid Algorithms for denoising the images captured by sensors. These algorithms use the DCT and DWT transforms for processing and take advantage of both transforms. These algorithms help in reducing false contouring and blocking articrafts effectively. Among these for a noisy satellite image, the Hybrid DWT-DCT algorithm proves to be a better choice as its PSNR has increased atleast by 13.5%, MSE and Coefficient of Variance is minimum and SSIM and MSSIM are improved when compared to DCT, DWT and Hybrid DCT-DWT Algorithms. Also the denoised images prove to have less noise in the images.

REFERENCES

1. R. Koenen, Ed., "Overview of the MPEG-4 standard," ISO/IEC JTC/SC29/WG21, Seoul, Korea, MPEG-99-N2925, Mar. 1999.
2. A. Said and W. Pearlman, "Low-complexity waveform coding via alphabet and sample-set partitioning in visual communications and image processing," in Proc. SPIE, 1997, pp. 25– 37.
3. S.-T. Hsiang and J. W. Woods, "Embedded image coding using zeroblocks of subband/wavelet coefficients and context modeling," in Proc. ISCAS 2000 Geneva Circuits and Systems, vol. 3, 2000, pp. 662–665.
4. R.Costantini, J.Bracamonte, G.Ramponi, J.L.Nagel, M.Ansorge, and F.Pellandini, "Low complexity video coder based on discrete Walsh Hadamard transform," in Proc. European signal processing conference, 2002, pp. 1217–1220.
5. M. Ezhilarasan and P. Thambidurai, "A hybrid transform technique for video coding," LNCS, vol. 4308, pp. 503–508, 2006.
6. U. S. Mohammed, "Highly scalable hybrid image coding scheme," Digital Signal Processing,Science Direct, vol. 18, pp. 364–374, 2008.
7. U. S. Mohammed and W. M. Abd-elhafiez, "Image coding scheme based on object extraction and hybrid transformation technique," Int. J. of Engineering Science and Technology, vol. 2, no. 5, pp. 1375–1383, 2010.
8. T.-H. Yu and S. K. Mitra, "Wavelet based hybrid image coding scheme," in Proc. IEEE Int Circuits and Systems Symp, vol. 1, 1997, pp. 377–380.
9. R. Singh, V. Kumar, and H. K. Verma, "DWT-DCT hybrid scheme for medical image compression," Medical Engineering and Technology, vol. 31, pp. 109–122, 2007.
10. F. Zhijun, Z. Yuanhua, and Z. Daowen, "A scalable video coding algorithm based DCTDWT," in Proc. 3rd IEEE Int. Symp. Signal Processing and Information Technology, 2003, pp. 247–249.
11. P. J. Paul and P. N. Girija, "A novel VLSI architecture for image compression," in Proc. ISM'06 Multimedia Eighth IEEE Int. Symp, 2006, pp. 794–795.
12. K. A. Wahid, M. A. Islam, S. S. Shimu, M. H. Lee, and S. Ko, "Hybrid architecture and VLSI implementation of the Cosine-Fourier-Haar transforms," Circuits, Systems, and Signal Processing, vol. 29, no. 6, pp. 1193–1205, 2010.

*Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication*