An Efficient Method for Periodic Vertical Banding Noise removal in Satellite Images

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***Abstract*— Images obtained by satellites are useful in many environmental applications such as tracking of earth resources, geographical mapping etc. These images are often corrupted by noise during their acquisition and transmission. Satellite images contain a special type of periodic noise called striping or banding noise. Numerous methods have been presented in the literature to remove the banding noise. These methods besides removing noise also tend to blur the images. In this thesis work an attempt is made to develop such algorithm in which the image quality is retained to the maximum extent. This method is based on two transforms DWT and DCT, both having very good decorrelation power to decorrelate the noise from the grayscale images.**

Keywords-Periodic noise,Fourier transform,Discrete wavelet transform,Banding noise

I. Introduction

Periodic vertical banding noise (PVBN) or striping noise is that noise which repeats the stripes/thin lines after a fixed interval, known as period of noise. Strip means a fixed value known as offset is added at that position and period means no offset is added at that point. Let the original image be F(x, y), then noisy image F'(x, y) containing banding noise of width w= (xe-xa) +1 and time period T is defined as

$$\text{PVBN} = \left\{ \begin{array}{ll} A & \text{for } x \ \varepsilon\ [xa.......xe] \\ 0 & \text{for } x \ \varepsilon\ (xe......w+T] \end{array} \right\} \quad ...(1)$$

Where A is the offset value to be added. This process is repeated for entire image.

So noisy image is F'(x, y) = F(x, y) + PVBN ... (2)

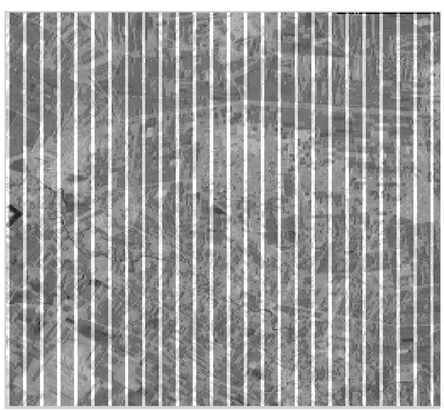


Figure 1: Periodic Vertical Banding Noise

So this noise depends on 3 parameters.

a) Band/Strip width: The width of the band /strip in the noise. It is measured in terms of pixels. The more is the strip width, more strong the noise is.

b) Time period: It is the period for which the offset value is zero, means the original pixels are not changed. It is measured in terms of number of pixels.

c) Offset: This is the intensity value to be added into the image. Larger offset means the strong noise and more contaminated image.

II. PERIODIC BANDING NOISE REMOVAL METHODS

A. Spatial domain methods

A traditional way to remove noise is by using the spatial filters means by working in the same space of co-ordinates. These techniques include the method such as mean filter, histogram adjustment, moment matching etc.

a) Histogram matching

Suppose every sensor has the same balanced radiation distribution, the sub image histogram of every sensor is adjusted by histogram adjustment [16] to one reference adjustment to realize noise reduction. The precondition of this method has much limit and not use when the involutedly surface contains different objects.

b) Moment Matching

Moment matching [6] is the next usual method of noise reduction. Suppose that objects detected by each sensor have the same balanced radiation distribution, and the noted data change has linear relationship with plus and excursion of radiation distribution. Then stripped noise reduction can be achieved by adjusting mean standard deviation of each sensor to certain reference value. This method is better than histogram adjustment. However, when small image or complicated objects can cause grey distribution asymmetrical, this method usually has “zonal effect”, which does not accord with distribution rule of natural geography element.

c) Low Pass Filtering

`In this technique low pass filter is employed, so high frequency stripes are eliminated while the original image data is retained. As it is assumed to be of low frequency. It works well with high frequency periodic noise.

B. Frequency Domain Methods

It means the image pixels values are transformed in other coordinates for evaluation and then thresholding or filtering is applied to reject noise and again image is converted into same coordinates. Fourier transform and DWT are the methods used in this category. For periodic noise, spatial domain filtering doesn’t work well, so transform domain methods are well suited for them. It is also known as transform domain methods.

a) Discrete Fourier transform

The DFT (Discrete Fourier transform) is the sampled Fourier Transform and therefore does not contain all frequencies forming an image, but only a set of samples which is large enough to fully describe the spatial domain image. The number of frequencies corresponds to the number of pixels in the spatial domain image, i.e. the image in the spatial and Fourier domains are of the same size.

For a vector f(x) of size N, the One-dimensional (1 D) DFT is given by:

$$F(u) = \sum_{x=0}^{N-1} f(x).\, e^{-i2\pi\left(\frac{ux}{N}\right)} \qquad \ldots(3)$$

Similarly 2D DFT for a matrix of size M X N is given as

$$F(u, v) = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y).\, e^{-i2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)} \qquad \ldots(4)$$

Where f(x, y) is the image in the spatial domain and the exponential term is the basis function corresponding to each point F(u, v) in the Fourier space. The equation can be interpreted as: the value of each point F(u) is obtained by multiplying the spatial image with the corresponding base function and summing the result. The basis functions are sine and cosine waves with increasing frequencies, i.e. F(0,0) represents the DC-component of the image which corresponds to the average brightness and F(N-1,N-1) represents the highest frequency.

In a similar way, the Fourier image can be re-transformed to the spatial domain. The inverse Fourier transform is given by:

$$f(x, y) = 1/(M*N) \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} F(u, v).\, e^{i2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)} \qquad \ldots(5)$$

It is common to multiply the image by $(-1)^{x+y}$ prior to computing the FFT .This shifts the centre of Fourier transform to (u/2,v/2).

$$F\,[f(x, y)\,(-1)^{x+y}] = F(u-M/2, v-N/2) \qquad \ldots(6)$$

In the frequency domain F(X, Y) of f (x, y), ideal vertical stripes include high frequency parts in the horizontal direction X, while in the vertical direction y’ after the 2D FFT, so there are no frequency components stemming from vertical stripes in Y≠0. Consequently by eliminating the Fourier coefficients F(X, Y) of f (x, y) at all X for Y= 0, the entire information arising from ideal vertical stripes will be erased. A better approach is proposed by Aizenberg [1] by using noise suppression median filter to suppress periodic vertical stripes.

b) Discrete Wavelet transform (DWT)

Discrete wavelet transform is a mutiresolution approach in which the image is first divided into four sub-bands i.e. Cl (Approximation sub band), Ch (Horizontal detail sub band), Cv(vertical detail sub band) and Cd(Diagonal detail sub band by use of filter bank. To obtain the next coarse scale wavelet coefficient, the sub-band Cl is further decomposed and critically sub-sampled. This process continues depending on the level specified are successively detached from all remaining image components.

Daubechies- Daubechies wavelet transforms are defined in the same way as the Haar wavelet transform by computing the running averages and differences via scalar products with scaling signals and wavelets the only difference between them consists in how these scaling signals and wavelets are defined. This wavelet type has balanced frequency responses but non-linear phase responses. Daubechies wavelets use overlapping windows, so the high frequency coefficient spectrum reflects all high frequency changes. Therefore Daubechies wavelets are useful in compression and noise removal in digital images.

Daubechies 4 wavelet coefficients are given as

$g = (g0, g1, g2, g3) = \quad (1+\sqrt{3})/4\sqrt{2}, (3+\sqrt{3})/4\sqrt{2}, (3-\sqrt{3})/4\sqrt{2}, (1-\sqrt{3})/4\sqrt{2}$

and $h=(h0,h1,h2, h3) = (g3,-g2,g1,-g0)$ …(7)

where g defines the low pass filter and h defines the high pass filter to be used in the filter bank to decompose using DWT.

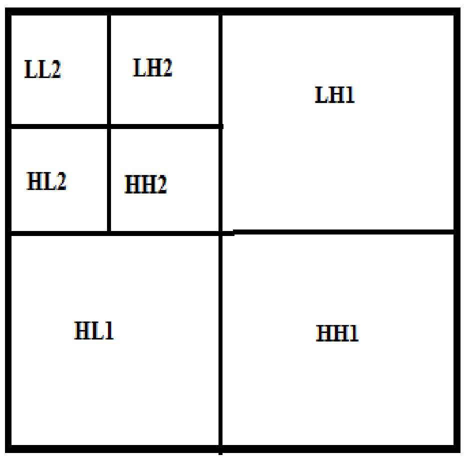


Figure 2: 2 D DWT decomposition into 2 levels

DWT is characterized by wavelet type and level of decomposition.

Wavelet Type- A wavelet is a waveform of effectively limited duration that has an average value of zero. They are irregular and asymmetric in nature classified on the basis of filter length used and number of vanishing points. Vanishing moment refers to the ability of wavelet to represent polynomial behavior in the signal. Example Daubechies 4 with two vanishing moments can easily encode constants and linear components. For a particular application i.e. for any signal the used wavelet function frequency should match the signal as closely as possible. In case of banding noise daubechies outperforms [15] all other wavelets. There are different types of wavelets in wavelet family such as:

i. Haar
ii. Daubehies
iii. Symlets
iv. Coiflets
v. Discrete Meyer transform

Level of decomposition-Level of decomposition also depends on the signal being analyzed. Generally high level of decomposition increases the performance in case of denoising the banding noise. But at a certain level the performance will become constant and further increasing the level will just add complexity to the method.

Consequently, the information from vertical stripes is exclusively condensed to C v,l,m,n and to the coefficients of the finally remaining low frequency band c l L,m,n. Due to the dyadic fractionation of the spatial extensions of the wavelet basis functions , each successive vertical details band Cv,l,m,n, $l \in \{1, \cdots ,L\}$ is basically comprising a frequency band of dyadically decreasing focal frequency . Accordingly, the amount of detached stripe information enclosed in Cv,l,m, n at each decomposition level l depends on the spatial frequency spectrum of the stripes in horizontal direction, which correlates with the stripe width. Hence, the highest decomposition level L required is coupled with the maximum expected stripe width. For a sufficiently large L, the impact of the stripe information to the low pass coefficients cl L,m,n becomes negligible. Blanking of c v,l,m,n at some selected l and subsequent inverse wavelet transform of the remaining wavelet coefficients will yield a modified version of (x,y), where vertical stripes are eliminated. This approach, here further refereed as "wavelet filter", has already been proposed and applied to satellite images.

c) FWT (Fourier wavelet transform)

This approach proposed by Prasad [15] uses the combined concept of DFT and DWT. It works as follows for vertical stripes-

i. Take the noisy input image.
ii. Apply DWT on it, to divide the image into approximation, horizontal and vertical sub bands depending on the level specified for decomposition.
iii. As vertical sub band will contain most of the vertical strip information, so apply 2D FFT on each of the vertical band.
iv. Then on these Fourier coefficients apply Gaussian function to filter out the noise.
v. Then perform inverse FFT again to convert it into spatial domain.
vi. Apply inverse wavelet transform to combine and reconstruct the image using all sub bands (including vertical, horizontal and detail sub bands.)

This approach has advantage of not losing high frequency details as FFT is applied only on vertical sub bands, so high frequency information is retained.

III. DISCRETE COSINE TRANSFORM

Discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. Discrete Cosine Transform (DCT) attempts to decorrelate the image data. After decorrelation each transform coefficient can be treated independently depending upon whether it is noise or original data. In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry. So computationally much simpler than FFT.

The most common DCT definition of a 1 -D sequence of length N is:

$$C(u)=a(u)\sum_{x=0}^{N-1} f(x)\ \mathrm{Cos}\left(\frac{(2x+1)\pi u}{2N}\right) \quad \text{…(8)}$$

where u=0,1,2,…………..N-1

Similarly, the inverse transformation is given by

$$F(x)=\sum_{u=0}^{N-1} a(u)C(u)\ \mathrm{Cos}\left(\frac{(2x+1)\pi u}{2N}\right), \quad \text{…(9)}$$

Where x=0,1,2,3……N-1

Where a(u) is defined as

$$a(u) = \begin{cases} \sqrt{(1/N)} & \text{for } u=0 \\ \sqrt{(2/N)} & \text{for } u\neq 0 \end{cases} \quad \text{…(10)}$$

Properties of DCT Beneficial to the Proposed Solution are:

a) Energy compression

DCT has been proven to have better energy compression efficacy than DFT. Efficacy of a transformation scheme can be directly gauged by its ability to pack input data into few coefficients. DCT exhibits excellent energy compaction for highly correlated images, which provides less frequency coefficient modification in the filtering procedure. The periodic information that has a fixed frequency is gathered in the frequency domain. As a result, the better the energy compression property, the less the frequency coefficients need to be reduced. Block artifacts can be directly reduced thereby preserving more image information.

b) Real Transform

DCT is a real transform while DFT is complex. DFT transforms a complex signal into its complex spectrum. However, when the signal is real, which is always true in a digital image application, half of the data is redundant. In the time domain, the imaginary part of the signal is all zero. In the frequency domain, the real part of the spectrum is even symmetry and the imaginary part is odd symmetry. On the other hand, DCT is a real

transform that transforms a sequence of real data points into its real spectrum and therefore avoids the problem of redundancy.
Due to these properties of DCT, it is preferred over DFT.

IV. PROPOSED METHOD

A new algorithm in frequency domain is proposed in which the noisy input image is taken as input. DWT with 4 levels of decomposition and Db4 as wavelet type are applied on the input image. Daubechies wavelets are selected as Prasad [15] mentioned that daubechies outperforms in case of vertical banding noise as compared to other wavelets.Db4 (Daubechies of order 4) is selected as it provides better performance (table 1) than daubechies of other orders. DWT will separate out the vertical band information into its 4 vertical sub bands, and then DCT is applied on each of these bands due to less calculation involved in it as compared to DFT.

Due to the periodic nature of noise and vertical nature of stripes, this information gets condensed into central row of Fourier spectrum due to shifting of fourier spectrum's DC component to center by fftshift( ) function. Now the noisy coefficients are condensed in the central row in form of peaks of each of the 4 vertical sub bands. The center is calculated from the size of each of this sub bands. Now on the central row, starting from first pixel to end, a median filter of size 3X3 is applied and a ratio of the coefficients current value to the median calculated at that point is computed. Now if this ratio is greater than some threshold then this coefficient is replaced by median calculated. As periodic noise have strong peaks, means coefficient's value is much larger than its neighbors, In the paper Aizenberg [1], it is estimated that for 3X3 filter this value is generally closer to 4.

The steps for proposed algorithm are given below:

Step 1: Take the noisy input image.

Step 2: Apply DWT on it, to divide the image into approximation, horizontal and vertical sub bands depending on the level specified for decomposition.

Step 3: For each decomposition level

a) Apply DCT on its vertical detail subband

b) Now apply median filter of size 3X3 on the center row of these vertical detail subbands. For each central row of vertical band

If the ratio r

$$r = \text{coefficient value}/\text{median} > p \qquad \dots (11)$$

The value of p is taken as 4 according to Aizenberg [1] .Then replaces coefficients value with median calculated.

c) Perform Inverse DCT of all the vertical detail subbands.

Step 4: Reconstruct the image by combining all the vertical bands with horizontal detail subbands, Diagonal detail subbands and approximation parts.

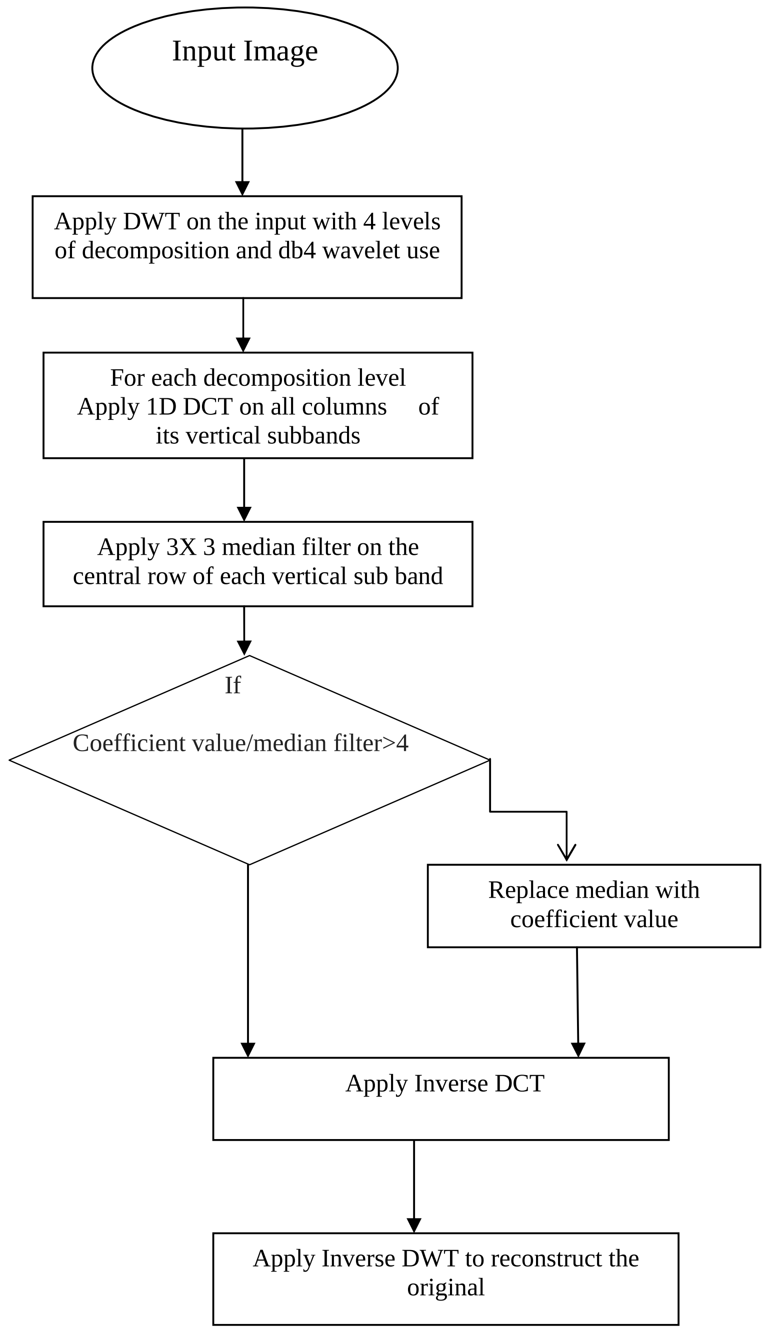
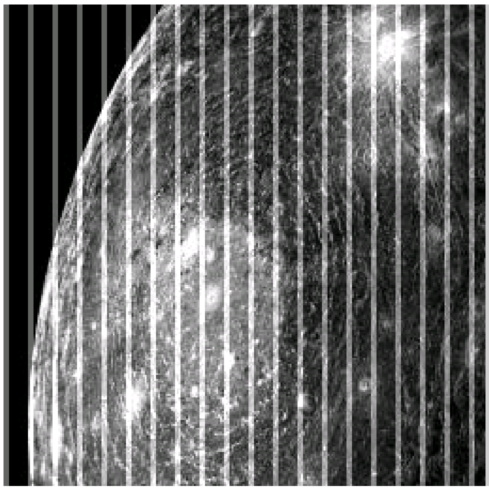


Figure 3: Flowchart of Proposed work

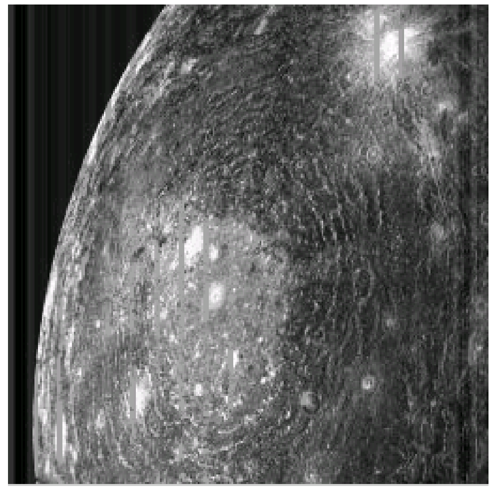
In the combination method of DWT and Fourier transform. DWT (Discrete wavelet transform) is first applied on the image with specified levels of decomposition, to separate out vertical frequency components in vertical sub bands, so all the vertical stripes information gets condensed into vertical sub bands, now 1D DFT (Discrete Fourier transform) is applied column wise to further compact the noisy coefficients, and then the horizontal row containing noisy stripes is damped by setting all the coefficients to zero. In the proposed method the 1D DFT is replaced by 1D DCT due to its computational simplicity and better energy compaction as given by huang [9]. DWT is performed at level of decomposition=4, as further increasing the level will not increase the performance, rather will increase the computations and the complexity of the algorithm. The concept of damping (setting all values to zero) is now replaced with the median concept. 3X3 median is selected to convolve the noisy row in frequency spectrum .if the ratio of coefficient's value to median calculated at that coefficient is greater than 4 and then this value is replaced by median as given by Aizenberg [1]

V. RESULTS AND DISCUSSION

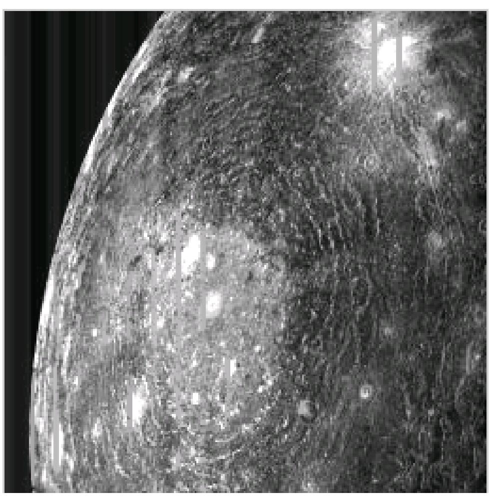
To measure the qualitatively as well as quantitatively performance of the proposed algorithm, some metrics are needed. For evaluating the proposed work, two metrics are used: Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE). The proposed algorithm is tested on standard image of size 256X 256 .Periodic vertical banding noise is added onto this image by using strip width, offset value and time period as variable parameters .The proposed algorithm is compared with Fourier transform method of Aizenberg [1] and combination of DWT with Fourier method of Prasad [15]. In Fourier transform method the DFT in of the original image is taken, due to vertical lines and periodic nature, these line will be concentrated in a horizontal row in form of peaks Fourier spectrum .These peaks are then modified by the use of 3X 3 median filter, where the Fourier coefficients whose value is much larger than median calculated is replaced by the median.



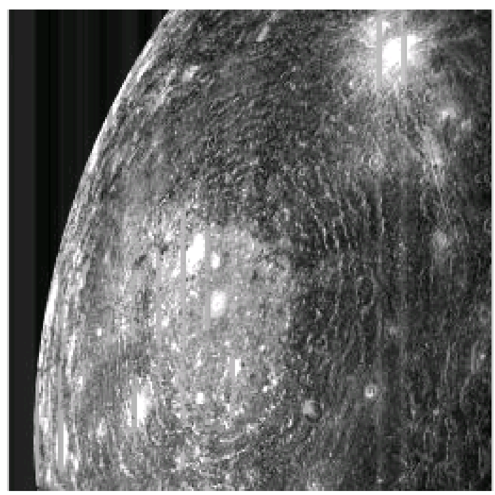
(a) Noisy Image



(b) Denoised image by Fourier transform method



(c) Denoised image by combination of DWT and Fourier transform



(d) Denoised Image after applying proposed algorithm

Figure 4: Comparison Results for denoising at noise parameters as: stripe width=3, Time Period=10 pixels and offset value=100

According to Prasad[15] Daubechies wavelets outperforms as compared to other wavelet (in case of vertical banding noise, so daubechies wavelets of different orders are compared in table 1, It is found that db4 offers maximum performance in almost all cases. So the wavelet db4 is used in all the further tables for comparison. The Figure 1 shows the results of proposed algorithm and the previous two methods. The results consist of noisy image, denoised image by Fourier, denoised image by DWT and Fourier combination method and after applying proposed algorithm.The values of PSNR and MSE tested on the test images at different factors such as strip width, time period and offset value are shown in the table 2 to table 10.For image quality to be better the Peak signal-to-noise ratio (PSNR) between the original and denoised image should be high and Mean Square Error (MSE) between the two images should be as low as possible. So, it is clear from the tables below that the PSNR values of various images at various factors are higher and MSE values are less for proposed method than previous two methods. The figure 4 clearly show that the results using proposed algorithm are visually better than previous methods discussed and tables 2 to 10 shows the improved PSNR and MSE values for the test image using different values of different factors

Table 1: Comparison of different order daubechies wavelets for the proposed method

Stripe width and Time period (in pixels)	**PSNR (Peak signal to noise ratio)**				
	Db4	**Db8**	**Db12**	**Db16**	**DB20**
Stripe width=1 Time period=1	14.74	14.67	14.72	14.72	14.73
Stripe width=1 Time period=2	18.21	18.26	18.24	18.23	18.26
Stripe width=1 Time period=5	24.36	24.08	24.32	24.35	24.44
Stripe width=1 Time period=10	29.31	27.96	28.68	28.70	28.87
Stripe width=2 Time period=1	12.14	12.13	12.14	12.14	12.14
Stripe width=2 Time period=2	14.74	14.71	14.69	14.69	14.72
Stripe width=2 Time period=5	19.67	19.43	19.51	19.51	19.56
Stripe width=2 Time period=10	24.12	23.94	24.07	23.99	24.00
Stripe width=3 Time period=1	11.15	11.11	11.11	11.11	11.13
Stripe width=3 Time period=2	13.06	13.03	13.08	13.09	13.06
Stripe width=3 Time period=5	17.30	17.14	17.23	17.23	17.23
Stripe width=3 Time period=10	21.26	20.99	21.26	21.36	21.30

Table 2: Improved PSNR and MSE implemented on strip width=1 pixel, offset=50

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	19.36	20.07	21.05	.0116	.0098	.0078
2	22.30	23.25	24.63	.0059	.0047	.0034
5	26.76	28.40	30.84	.0021	.0014	.0008
10	29.62	31.59	34.38	.0011	.0006	.0003

Table 3: Improved PSNR and MSE implemented on strip width=2 pixels, offset=50

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	17.05	17.62	18.31	.0197	.0173	.0147
2	19.36	20.08	21.01	.0116	.0098	.0079
5	23.21	24.51	26.09	.0048	.0035	.0025
10	26.12	28.30	29.99	.0024	.0015	.0010

Table 4: Improved PSNR and MSE implemented on stripe width=3 pixels and offset=50

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	16.13	16.67	17.30	.0243	.0215	.0186
2	17.84	18.49	19.28	.0164	.0141	.0118
5	21.57	22.42	23.67	.0070	.0057	.0043
10	24.51	26.03	27.58	.0035	.0025	.0017

Table 5: Improved PSNR and MSE implemented on stripe width=1 pixel and offset =75

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	16.15	16.67	17.30	.0243	.0215	.0186
2	19.23	19.92	20.83	.0119	.0102	.0083
5	24.00	25.45	27.04	.0040	.0028	.0020
10	27.43	29.38	31.83	.0018	.0012	.0045

Table 6: Improved PSNR and MSE implemented on strip width=2 pixels, offset=75

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	13.79	14.19	15.59	.0418	.0380	.0276
2	16.15	16.68	17.30	.0243	.0215	.0186
5	20.24	21.24	22.29	.0095	.0075	.0059
10	23.55	25.34	26.73	.0044	.0029	.0021

Table 7: Improved PSNR and MSE implemented on and stripe width=3 pixels, offset=75

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	12.85	13.24	14.28	.0518	.0474	.0373
2	14.62	15.08	15.59	.0345	.0310	.0276
5	18.43	19.08	20.01	.0143	.0124	.0101
10	21.59	22.85	23.91	.0069	.0052	.0041

Table 8: Improved PSNR and MSE implemented on strip width=1 pixel, offset=100

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	13.86	14.28	15.08	.0411	.0373	.0310
2	16.99	17.53	18.21	.0200	.0176	.0151
5	21.89	23.17	24.36	.0065	.0048	.0037
10	25.48	27.40	29.31	.0028	.0018	.0012

Table 9: Improved PSNR and MSE implemented on strip width=2 pixels, offset=100

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	11.48	11.80	12.14	.0710	.0660	.0610
2	13.86	14.28	14.74	.0471	.0373	.0335
5	18.07	18.87	19.67	.0156	.0130	.0108
10	21.53	23.05	24.12	.0070	.0049	.0039

Table 10: Improved PSNR and MSE implemented on strip width=3 pixels, offset=100

Time period (in pixels)	DFT	DWT+DFT	Proposed method	DFT	DWT+DFT	Proposed method
	PSNR(in db)			MSE		
1	10.53	10.84	11.15	.0883	.0823	.0767
2	12.34	12.68	13.06	.0583	.0539	.0493
5	16.17	16.69	17.30	.0241	.0214	.0186
10	19.52	20.50	21.26	.0759	.0089	.0075

VI. PERFORANCE METRICS

Performance is evaluated by calculating Peak Signal to noise ratio (PSNR) between original image and noisy image.

1. MSE = $\sum\sum ((x(i, j) - y(i, j))^2$

2. $$\text{PSNR} = \frac{10 * \log10(\max((x(i, j))^2))}{\text{MSE}}$$

Where x (i, j) be the original image and y (i, j) be the noisy image. MSE stands for mean square error.

VII. CONCLUSION

One of the most commonly used method of Fourier transform with median filter is described. Another method based on combination of DWT and DFT is considered for comparison. The proposed scheme combines these two approaches offering advantages of both the methods. In case of the Fourier transform method, replacing value with median is advantageous rather than setting their value to zero. The combination method DWT and DCT has the advantage that noisy coefficients are only in vertical sub band so the coefficient values of all other sub bands will not be changed. This will prevent the image from blurring as most of the coefficients are retained and are not changed, So performance will be better. The proposed method offers these two advantages and hence better performance as compared to these two methods.

REFERENCES

[1] Aizenberg, I. and Butakoff, C., 2001. “Frequency domain median like filter for periodic and quasi periodic removal,” Neural Network technologies Ltd.
[2] Amri ,S. , Kalayanker , N. and Khamitkar, S., 2010 .“A comparative study of removing noise from remote sensing images “,International journal of computer Science Issues, Vol. 7, No.1,pp. 32-36.
[3] Chavan, M. and Mastorakis, N. ,2010.” Studies on Implementation of Haar and daubechies Wavelet for Denoising of Speech Signal,” International Journal of Circuits, Systems and Signal Processing, Vol. 4, No. 3, pp. 83-96.
[4] Ellinas, J., Mandadelis, T., Tzortzis, A. and Aslanoglou L.”Image denoising using wavelets,” T. E .I of Piraeus, Department of electronic computer systems.
[5] Filho, C. and Dinniss, A., 2002.” Periodic noise suppression techniques applied to remote sensing images”, Boletim IG-USP, Série Científica.
[6] Gadallah, F. and Csillag, F., 2000.” Destriping multisensor imagery with moment matching”, International journal of remote sensing, Vol. 21, pp. 2505-2511.
[7] [Gonzalez, R. and Woods, R., 2011.” Periodic noise reduction by Frequency domain filtering,” Digital Image Processing, pp. 266-279.
[8] Hanling, H. and Wujing, W., 2009.” Study of noise filtering algorithm Experiment on spatial domain and frequency domain ofperspectral image”, International symposium on spatial analysis, Vol. 7492, pp. 7492(H1-H8).
[9] Huang B., 2010.” Removing Textured Artifacts from Digital Photos Using Spatial Frequency Filtering”, MS Thesis, Portland state university, pp. 1-63.
[10] Huang, P., Su, S. and Tu, T., 2004.”A destriping and enhancing technique for remote for EROS remote sensing imagery,” Journal of C.C.I.T, Vol. 32,No.2, pp. 1-14.
[11] Hudhud ,G. and Turner, M., 2005., ” Digital Removal of Power Frequency Artifacts Using a Fourier Space Median Filter”, IEEE Signal Processing Letters, Vol. 12, No. 8, pp. 573-576.
[12] Ji, Z., Liao, H., Zhang, X. and Wu, Q., 2006.” Simple and Efficient soft morphological filter in periodic noise reduction”, Institue of Electical and Electronics Engineering.
[13] Mahmoud, M .,Dessouky, M., Deyab, S. and Elfouly, F., 2007. “Comparison between Haar and Daubechies Wavelet Transformions on FPGA technology,” World Academy of Science, Engineering and Technology 26.
[14] Patil, S., Patil, A., Deshmukh, S. and Chavan, M., 2010.” Wavelet Shrinkage Techniques for Images,” International Journal of Computer Applications, Vol. 7, No.1, pp. 7-11.
[15] Prasad, R., Sreenivasu, T. and Rao, M., 2011.” PoWer: Polar Wavelet-Gaussian Filter for ring artifact suppression in CT Imaging Systems”, International Journal of Computer Science & Communication Networks, Vol. 1,No. 2, pp. 186-195.
[16] Rakwatin, P., Takeuchi, W. and Yasuoka Y., 2007. “Strip noise reduction in MODIS data by combining histogram matching with facet filter”, IEEE transaction on Geo Science and remote sensing, Vol. 45, No. 6 ,pp. 1844-1855.
[17] Ruikar, S. and Doye D., 2011.” Wavelet Based Image Denoising Technique”, International Journal of Advanced Computer Science and Applications, Vol. 2, No.3, pp.49-53.
[18] Sandhu, R. and Maan , P., 2011. ”A spatial domain filter for digital image denoising used for real time applications”, International journal of computer science and technologies, Vol. 2,No. 3,pp. 125-129.
[19] Tewari, B., Dubey, S. and Nizamuddin M., ”Compression analysis between DWT and DCT”, IT and business intelligence.
[20] Tsai, F. and Chen W., 2008.” Striping Noise Detection and Correction of Remote Sensing Images”, IEEE Transactions on Geoscience and remote sensing, Vol. 46, No. 12, pp. 4122-4131.
[21] Wang, J. and Liu D., 2006. ” 2 D FFT for periodic noise removal in strain image”, Institute of Electrical and Electronics Engineering.
[22] Yan, C., Xian, Z. and Jun, L., 2008. ”Study on methods of noise reduction in a stripped image”, The international archives of the photogrammetry, Remote sensing and spatial information Sciences, Vol. 37. Pp. 213-216.