

A Systematic Approach for Image Enhancement on Landsat8 Imagery

K. Sateesh Kumar¹, G. Sreenivasulu²

¹Research Scholar, Department of Electronics and Communication Engineering,
Sri Venkateswara University College of Engineering, S V University, Tirupati, Andhra Pradesh, India

²Professor, Department of Electronics and Communication Engineering,
Sri Venkateswara University College of Engineering, S V University, Tirupati, Andhra Pradesh, India

Abstract —This paper proposes the systematic approach for de-noising of remote sensing imagery. In this study, we have utilized Landsat8 Dataset. As a first step, estimated the Additive White Gaussian Noise level (AWGN) using Block based Singular Value Decomposition (BSVD) approach. Denoise this imagery with the help of Dual-Tree Complex Wavelet Transform (DT-CWT) coefficients and further enhance the image using Bilateral Filter. Our proposed method was compared with the state of art denoising methods on the basis of Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM) with existing methods and proved that this technique achieves the good statistics and quality too.

Keywords-Additive White Gaussian Noise, Block based SVD approach, Dual Tree Complex- Wavelet Transform, Bilateral Filter.

I. INTRODUCTION

Noise is one of the main elements that could be avoided in signal/Image processing domain. In general, Prior knowledge about the noise is essential for denoising of images. Image De-noising involves so many techniques [1-5] Singular Value Decomposition (SVD) is also one of them. There must be a specific algorithm, to decide whether the noise is due to illumination, colour or texture variations. This work has been prepared as an extension for the work [6]. Basically, attack of noise is one of the two types i.e., Additive or Multiplicative. The fundamental equations for these noise types are represented in eq. (1) and (2).

$$Y(x, y) = X(x, y) + N(x, y) \quad (1)$$

$$Y(x, y) = X(x, y) * N(x, y) \quad (2)$$

Where, X, N and Y are Input Image, Noise intensity and output images respectively. x and y represent the location of the pixel. Actually, N is independent of input image. For the sake of simplicity, we have considered an AWGN noise attack. The generalized equation for Gaussian Noise is given in eq. (3).

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (3)$$

Where, σ represents Noise Standard Deviation, μ is the mean of the noise. For Zero Mean Additive Gaussian noise ($\mu = 0$). So, obviously the entire distribution depends on the noise standard deviation. Out of three AWGN estimation methods (i.e., Filter based, block based and transform based) block based discussed in this paper. Discrete Wavelet (DWT) extensively has a number of applications in Denoising, Fusion and Enhancement [7-10]. It decomposes the image into four bands LL, LH, HL and HH by row and column wise. Dual-Tree Complex Wavelet has been elaborately discussed in this paper. Conceptually, Dual tree DWT consists of two separable DWT and for Complex Dual Tree DWT (DT-CWT) [11] there are four separable 1D DWT two for Row and Column and remaining two for Real and Imaginary coefficients respectively. It is oriented in six distinct directions. The nonlinear Adaptive Bilateral Filter (ABF) enhances the image with edge preservation. It deserves size and contrast of the image. It is weighted average denoising filter with followed edge variations.

The bilateral Filter (BF) is defined by [12]

$$BF[I_p] = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(\|I_p - I_q\|) I_q \quad (4)$$

Where W_p is a normalized factor given by

$$W_p = \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(\|I_p - I_q\|) \quad (5)$$

Where, σ_s and σ_r Measure the amount of filtering for input image $m(p, q)$.

G_{σ_s} is the spatial Gaussian factor, which varies inversely with distinct pixels.

G_{σ_r} is a range Gaussian factor, which decreases the influence of q pixel with an intensity different from I_p .

II. PROPOSED METHOD AND MATERIALS

The proposed method has the following three modules to solve the problem discussed in the last session. (i) Noise Estimation using Block based SVD approach. (ii) CT-DWT based Denoising and (iii) ABF based edge enhancement. In this section discuss about each module in detail.

2.1 Block Based SVD Approach For AWGN Estimation

To rectify the major challenges in the enhancement of remote sensing imagery, estimation of noise effect is vital step towards the target. For that we have used [13] BSVD based AWGN noise. With the help of Singular Value Decomposition (SVD). In this method entire image can be represented using three matrices, U, S and V. S is the matrix that represents the image details in statistics as a proportion of signal strength. Before going to into Block based SVD approach, let us have a look on SVD. The below eq.(6) Shows basic concept of SVD.

$$A = UXSX^T \quad (6)$$

Where $UU^T = I_{mm}; V^TV = I_{nn}$ (I_{mm} and I_{nn} denote the m-square and n-square identity Matrices. m and n represents the row and column of the image at. The columns of U are orthonormal Eigenvectors of AA^T , the columns of V are orthonormal Eigen vectors A^TA , and S is a diagonal matrix containing the square roots of Eigenvalues of AA^T or A^TA arranged in the descending order. This view is enough to focus on Block based SVD approach. The entire image has been divided into 'k' non overlapping blocks

$$r = \frac{m}{k}; c = \frac{n}{k} \quad r = \{1, 2, \dots, m\} \quad c = \{1, 2, \dots, n\} \quad (7)$$

Generally equal size of block is preferred. Use of Block based SVD is extracting the features of each block with separate Eigenvalues instead of the whole image. In real time, noise needs to spread over the image equally. So, by using BSVD there is a high chance of estimating the noise.

2.1.1 Estimation of AWGN.

To detect the effect of noise on original image SVD for both images calculated individually and compared with one another.

$$S_s = U^T X A_0 X V \quad (8)$$

$$S_n = U^T X A_n X V \quad (9)$$

Sincerely, noise is not identical to the signal. So there is a much variation between them. Graphically, it also has been represented in the figure. 1. It shows the comparison of Signal SVD components (S_s) and Noise SVD components (S_n) With noise level $\sigma=50$.

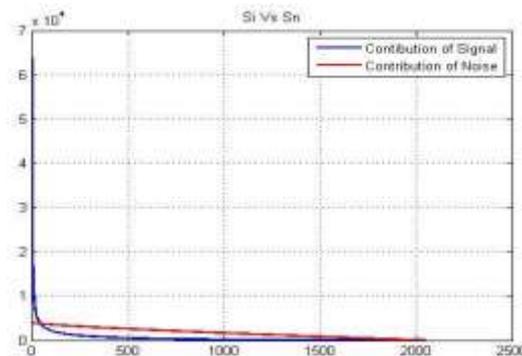


Figure 1. S_s Vs S_n Graph for image size 2048X2048

AWGN Analysis can be done using N be a zero-mean AWGN image with standard deviation σ and SVD is expressed as:

$$N = U X S_n X V^T \quad (10)$$

$$\sigma^2 = \sum_{t=1}^r S_n^2(i) \quad (11)$$

Now, M is to represent the number of the last singular values under consideration.

$$P_M(\sigma) = \frac{1}{M} \sum_{t=r-M+1}^r S_n(i) \quad (12)$$

Where $1 \leq M \leq r$, only the least singular value $S_n(r)$, when $M=r$, all singular values i.e., $S_n(1)$ to $S_n(r)$ are considered in above eq.(12). P_M is linearly dependent on σ .

$$P_M(k\sigma) = \frac{1}{M} \sum_{t=r-M+1}^r k S_n(i) = k X P_M(\sigma) \quad (13)$$

$$P_M(\sigma) = \alpha \sigma, \text{ where } M \gg 1 \quad (14)$$

Where α denotes the slope of the linear function which can be affected by the choice of M. If $M < r/4$, the attributes of AWGN will result the value of P_M .

$$P_M = \alpha\sigma + \beta \text{ and } P_{1M} = \alpha\sqrt{\sigma^2 + \sigma_1^2} + \beta \quad (15)$$

$$\hat{\sigma} = \frac{\alpha\sigma_1^2}{2(P_{1M} - P_M)} - \frac{P_{1M} - P_M}{2\alpha} \quad (16)$$

β is the variation of variance σ with effect of noise. $\hat{\sigma}$ is the estimation of standard deviation. The results of this stage are discussed in the section IV (Results).

2.2 Dual-Tree Complex Wavelet Transform (DT-CWT)

Once the estimation is over denoise it using DT-CWT with suitable coefficients. The noisy image decomposed into sub bands by using six levels of DT-CWT. The possible coefficients with phase information are $+75^\circ$, $+45^\circ$, $+15^\circ$, -15° , -45° and -75° [14-17]. For the first level, specially designed real filters with real coefficients were used. For the remaining levels, these phase coefficients were used. For this purpose, the sample process repeated 5 times for Real and Imaginary parts individually. The output is almost shift invariant and having good directional selectivity. The noisy subbands are denoised using the LA-BSF methodology. It requires prior knowledge about the noise type, for that purpose BSVD based approach was proposed in this paper. It estimated the denoised coefficients with the help of neighboring coefficients. A 5×5 and 7×7 window shows the best result over 3×3 . The below figure. 2 show the algorithm for the proposed DT-CWT based denoising method. As the preliminary step, the image is divided into real and imaginary components with possible phase values. Repeat the same for all phase combinations. Secondly, denoise using Local Adaptive Bivariate Shrinkage Function (LA-BSF) method and finally convert back the image (spatial domain) using inverse DWT. The outcomes of denoising algorithm discussed in the results section. It denoises the images at a particular threshold level in each iteration. The threshold value ranges from 1 to 50. Minimum threshold means an inaccurate decision of noise and high value represents the prominent gap between noise and signal.

2.3 Bilateral Filter

In general Bilateral Filter was used for denoising purposes, but interestingly modifications in existing bilateral filter results Adaptive Bilateral filter (ABF). General problem of BF is smoothing the edges. It is motive of the research to design edge preserved enhancing Filter. It rarely disturbs the colour map [18].

$$f[m, n] = \sum_i \sum_j h[i, j; m, n] g[i, j] \quad (17)$$

Where, $f[m, n]$ is the restored version of input image $h[i, j; m, n]$ at $[m, n]$ to impulse at $[i, j]$ and $g[i, j]$ is the degraded image.

$$r_{m_0 n_0} = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} e^{-\frac{(m-m_0)^2 - (n-n_0)^2}{2\sigma_d^2}} X e^{-\frac{(g[m,n] - g[m_0-n_0])^2}{2\sigma_r^2}} \quad (18)$$

Where, m_0, n_0 are represents the center pixel. $[m, n] \in [m_0-N, m_0+N] \times [n_0 - N, n_0 + N]$, σ_d and σ_r are factors of the filter.

It is a normalized expression that preserves the contrast of gray levels of the input image. It is a combined form of low pass filter (Gaussian) (GLPF) and range filter. This GLPF assigns more weight for the similar gray levels of the center pixel value [19].

2.3.1 Adaptive Bilateral Filter (ABF)

It is a new approach to image enhancement. It consists of two nonlinear filters, i.e., Domain Filter and Range Filter. Domain filter assigns the greater weight in the near around the value of central pixels. The range filter acts as a derivative filter to preserve the edges.

It can be expressed mathematically using below equation.

$$r_{m_0 n_0} = \sum_{m=m_0-N}^{m_0+N} \sum_{n=n_0-N}^{n_0+N} e^{-\frac{(m-m_0)^2 - (n-n_0)^2}{2\sigma_d^2}} X e^{-\frac{(g[m,n] - g[m_0-n_0] - \zeta[m_0-n_0])^2}{2\sigma_r^2 [m_0-n_0]}} \quad (19)$$

The main difference between equation and eq. is adding $\zeta[m_0 - n_0]$ Term in the range filter's normalized equation. Based on the value of ζ it can works as normal BF or ABF and only range filter. If $\zeta=0$ and real component ζ_r is fixed at threshold ABF is locally adaptive in nature acts as normal BF. For the operation of domain filter, deviation in σ_d Should be adopted in the ABF. The combo of these two parameter variations can boost up the filter with smoothing and sharpening.

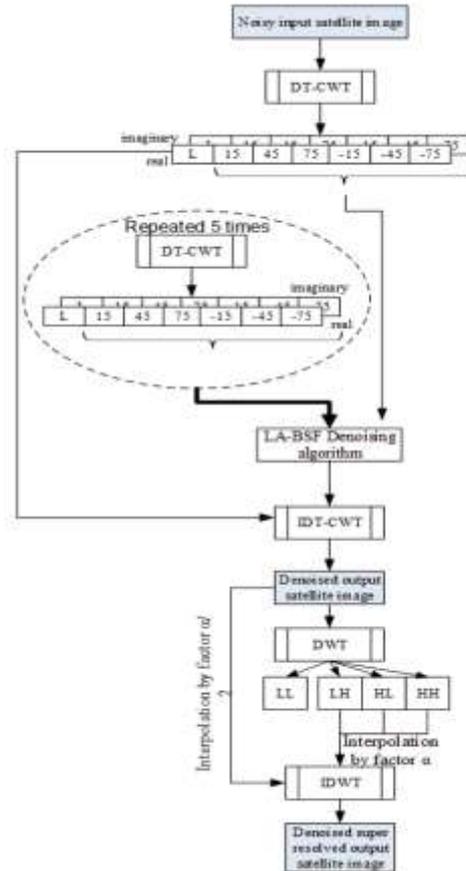


Fig 2. DT-CWT Methodology

The material of Landsat Data has been collected from the USGS website. Images of Chittoor region are having path and row of 144/145 and 50/51 respectively. Fig 3 shows the image set (Some part of Chittoor District, AP, India)

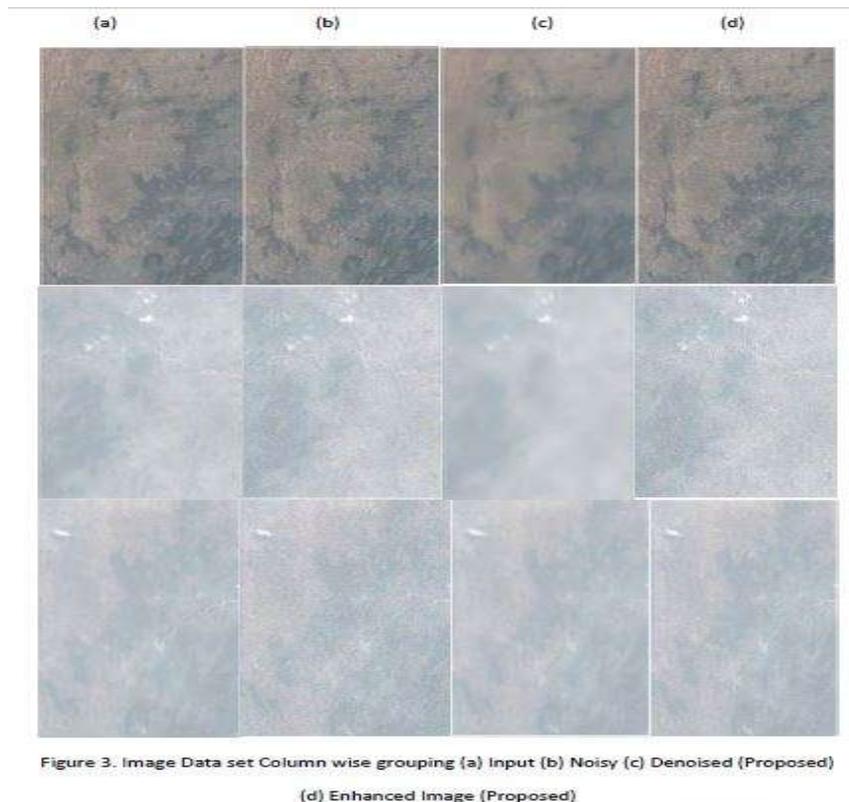


Figure 3. Image Data set Column wise grouping (a) Input (b) Noisy (c) Denoised (Proposed) (d) Enhanced Image (Proposed)

III. RESULTS AND DISCUSSIONS

The proposed method of BSVD AWGN estimation has been applied on Landsat Images. We have tested 50 images and estimated P_{1M}, P_M as the mean of corresponding SVD values. Statistically, most of the singular values are concentrated around $M=3r/4$. For the purpose of computing the performance data set is resized into 512 X 512 grayscale images for each band of landsat8. The available size of blocks and their estimation results are tabulated in the Table 1. Once the estimation is over the noisy image is to be denoised using DT-CWT algorithm and enhances the denoisy version of the imagery without smoothing and blurring impact. It systematically improves the edge details by enhancement using ABF. The figure 3. Shows the original image, noisy image denoised image and enhanced image at a glance. Variations of PSNR with respect to the threshold values is represented in Figure 4. From this figure, it is clear that at the early values of threshold, there this method getting peak PSNR and value is decreased by increasing the threshold level. So, it is better to keep threshold around 30. From the figure, it is very clear that the proposed system improves the PSNR with effectiveness.

The results of this section are tabulated in the table 2. From the table it can be derived that the proposed algorithm is best suitable for denoising Landsat8 over existing methods. For the performance comparison state of the art metrics were selected like PSNR and SSIM. The data set covers the entire year so that it indirectly tested the atmosphere conditions too.

Table 2. Comparison Of Standard Deviation For Image Set

Image #	Block size	Standard Deviation σ									
		10	20	30	40	50	60	70	80	90	100
1	128 X 128	9.87	19.83	29.71	39.69	49.50	59.27	69.25	79.13	89.07	99.78
	256 X 256	9.36	19.29	29.19	39.26	49.16	59.03	68.92	78.78	88.76	98.48
	512 X 512	10.9	20.05	30.01	40.29	50.1	60.11	71.17	80.05	90.18	100.16
	1024 X 1024	9.9	18.9	28.7	37	48	59	71	80	91	102
	2048 X 2048	10.88	20.56	30.98	40.8	51	62	71.5	82	93	105
2	128 X 128	8.87	18.82	28.72	38.5	48.4	58.3	68.19	78.16	87.9	97.84
	256 X 256	9.95	19.9	29.96	39.97	49.9	59.86	69.9	79.88	89.7	100.01
	512 X 512	10.06	20.06	30.08	40.04	50.08	60.09	70.11	80.16	90.24	100.2
	1024 X 1024	9.95	19.1	28.89	38.89	48.97	57.86	67.21	77.93	88	97.6
	2048 X 2048	8.9	17.5	28.7	36	47.2	56	66.9	77	87	96
3	128 X 128	8.81	19.2	28.74	36.99	47.31	58.1	68.7	78.01	86	96.3
	256 X 256	9.2	19.5	29.3	37.3	48.57	58.42	69.6	79.08	87.3	98
	512 X 512	10.01	20	30.12	40.1	50.02	60	70.09	80.11	90.12	100.88
	1024 X 1024	9.7	21	32	43	55	67	72	83	92.3	100.53
	2048 X 2048	10.5	20.9	30.6	40.91	50.77	60.34	70.43	80.79	91	101.01
4	128 X 128	7.1	18.82	28.72	38.5	48.4	58.3	68.19	78.16	87.9	97.84
	256 X 256	9.85	19.7	29.6	39.31	49.29	59	69.24	79.08	89.5	100.81
	512 X 512	10	20	30.4	40.9	50.2	60.22	70.4	80.1	90.05	100.2
	1024 X 1024	9.89	18.76	28.17	41	48.23	59.89	71	82.66	91.87	102
	2048x2048	11.9	19.5	29.33	39.81	49.25	62	70.36	81.05	87	96
5	128 X 128	8.5	18.9	29.8	38.41	46.88	58.9	69.22	79.13	89.6	97.07
	256 X 256	9.85	19.7	29.6	39.31	49.29	59	69.24	79.08	89.5	100.81
	512 X 512	10	20	30.9	40	50.8	60.11	70.9	80.3	90.9	100.4
	1024 X 1024	9.9	18.9	28.7	37	48	59	71	80	91	102
	2048 X 2048	8.9	17.5	28.7	36	47.2	56	66.9	77	87	96

Table 3. Comparison of proposed method with existing methods

Image #	PSNR (dB)			SSIM		
	DWT	Liu et al, [5]	Proposed	DWT	Liu et al, [5]	Proposed
1	61.1	63.7	65.99	0.89	0.93	1
2	69.6	70.4	77.6	0.85	0.91	1
3	75	82.1	89.97	0.87	0.9	0.99
4	76.2	78.1	89.33	0.85	0.91	0.98
5	62	83.7	87	0.86	0.9	0.99
6	75	77.4	84	0.85	0.92	0.99
7	69	73.9	78.12	0.88	0.94	1
8	76	84.7	87.87	0.87	0.92	1
9	62	66	78.99	0.86	0.91	0.99
10	61	69	76.12	0.84	0.93	1

IV. CONCLUSION

From this study, we can conclude that the proposed system is a systematic approach for diagnosing of landsat8 imagery starts from estimation to enhance. The three modules estimating the impact of noise, denoising and enhancement are developed with the help of Block based SVD approach, Dual Tree DWT and Adaptive Bilateral Filter. When we compared with previous techniques the proposed methods are efficient in the perspective of quality parameters like PSNR, and SSIM. From this study, we can conclude that Block based SVD provides better estimation of AWGN noise level.

From Table.1 shows the 512 X 512 block division proves the better resolution out of all available blocks. It covers the entire image with prominent estimation of noise level. On the other hand, denoising results are represented in Table 2. From this table, clearly observed that the proposed method effectively denoise the Landsat8 Image in real time. In addition to this design ABF enhances the image visually. So, this proposed method is a systematic approach for enhancement of Landat8 images in real time. Even though the data set cover lot of texture variations (Water body, Hilly area, Forest and buildings, etc.) the proposed system efficiently gains the enhancement. It overcomes the problems discussed in [3,5] by Dual tree approach. The existing methods failed to show that large scale of variations. The figure III. Shows the graphical -- representation for the variation of PSNR with the changing of threshold levels. From this figure PSNR has varied almost linearly for starting level of the threshold, but after certain range it fails to detect the noise in the imagery thereby a reduction in the quality of output. The proposed method stands good performance even though at higher threshold levels.

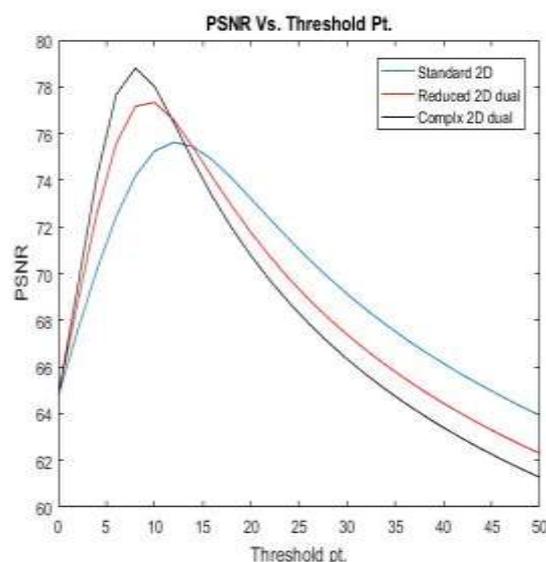


Figure 4. Variation of PSNR with Threshold level.

V. Acknowledgement

We personally thankful to Dr. B.Manikin, former Scientist, ISRO, Bangalore, K.V Chandrasekhar, Scientist, NRSC, Hyderabad for supporting us by giving guidance towards completion of the research paper. Sincere thanks to CoE (Centre of Excellence) team members, Faculty of SVUCE for their valuable guidance and support towards the successful completion of the paper.

VI. References

- [1] H. Demirel, C. Ozcinar, and G. Anbarjafari, "Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition", *IEEE Geoscience Remote Sens. Letters.*, vol. 7, no. 2, pp. 337, Apr. 2010
- [2] J. H. Jang, S. D. Kim, and J. B. Ra, "Enhancement of optical remote sensing images by subband decomposed multiscale retinex with hybrid intensity transferfunction", *IEEE Geosci. Remote Sens. Lett.*, vol. 8, no. 5, pp. 983–987, Sep. 2011
- [3] R. Atta and M. Ghanbari, "Low-contrast satellite images enhancement using discrete cosine transform Pyramid and singular value decomposition," *IET Image Process.*, vol. 7, no. 5, pp. 472–483, Jul. 2013.
- [4] E. P. Simoncelli and E. H. Adelson, "Noise removal via Bayesian wavelet coring", Proc. 3rd International Conference on Image Processing. Lausanne, Switzerland, 1996, pp. 379–382.
- [5] Wei Liu and Weisi Lin, "Additive white Gaussian Noise Level Estimation in SVD Domain for Images", *IEEE Transactions*, Vol 22 No 3, March 2013.
- [6] U. M. Gokhale, Y.V.Joshi, Noise Estimation Using Filtering and SVD for Image Tampering Detection- International Journal of Engineering Science and Innovative Technology (IJESIT) Volume 2, Issue 1, January, 2013.
- [7] Ranchin, T., and Wald, L, "Fusion of high spatial and spectral resolution images: the arsis concept and its implementation", *Photogrammetric Engineering & Remote Sensing*, 66(1), 2000. pp. 49-61.
- [8] Sunar, F., and Musaoglu, N., "Merging multiresolution SPOT P and Landsat TM data: the effects and advantages", *International Journal of Remote Sensing*, vol.19, 1998. pp.219–224.
- [9] Yong Yang, Dong Sun Park, Shuying Huang, and Nini Rao, "Medical Image Fusion via an Effective Wavelet Based Approach", *EURASIP Journal on Advances in Signal Processing* Volume 2010.
- [10] VPS Naidu, "Discrete Cosine Transform based Image Fusion techniques, " *Journal of Communication, Navigation and Signal Processing* (January 2012) Vol. I, No. I, pp. 35-45.
- [11] M Zafar Iqbal, A Ghafoor, A Siddiqui, M Mohsin Riaz, and Umar Khalid, "Dual-tree complex wavelet transform and SVD based medical image resolution enhancement", *Signal Processing*, 2 June 2014, pp.430.
- [12] C. Tomasi, R. Manduchi, "Bilateral filtering for gray and colour images", *IEEE Int. Conf. Computer Vision., Proc.* 1998.
- [13] K. Sateesh Kumar, G. Sreenivaslu and S. Varadarajan, "Block Based SVD approach for Additive White Gaussian Noise level Estimation in Satellite Images", *Proceedings of the IEEE International Conference on Computer*, October, 2016.
- [14] D. J. Jobson, Z.-U. Rahman, and G. A. Woodell, "A multiscale Retinex for bridging the gap between Colour images and the human observation of scenes", *IEEE Trans. Image Process.*, vol. 6, no. 7, pp. 965–976, Jul. 1997.
- [15] X. Fu, Y. Liao, D. Zeng, Y. Huang, X. Zhang, and X. Ding, "A probabilistic method for image enhancement with simultaneous illumination and reflectance estimation", *IEEE Trans. Image Process.*, Vol. 24, no. 12, pp. 4965–4977, Dec. 2015.
- [16] X. Zhu and P. Milanfar, "Automatic parameter selection for denoising algorithms using a no-reference measure of image content", *IEEE Trans. Image Process.*, vol. 19, no. 12, pp. 3116–3132, Dec. 2010.
- [17] W.L. Lee, C.C. Yang, H.T. Wu, M.J. Chen, "Wavelet-based interpolation scheme for resolution enhancement of medical images", *Journal of Signal Processing Systems*. 55 (2009) 251–265.
- [18] C. Tomasi and R. Manduchi, "Bilateral Filtering for Gray and Color Images", *Proceedings of the IEEE International Conference on Computer Vision*, Bombay, India, 1998.
- [19] Dogra A, Bhalla P. "Image Sharpening By Gaussian And Butterworth High Pass Filter". *Biomedical Pharmaceutical Journal*, 2014; 7(2)