A Color Image Enhancement based on Discrete Wavelet Transform

G. Saravanan
Assistant Professor
Dept. of Electrical Engineering
Annamalai University

G. Yamuna, Ph. D
Professor
Dept. of Electrical Engineering
Annamalai University

R. Vivek
Assistant Professor
Dept. of Electronics & Communication
MEFGI

ABSTRACT
It is proposed that a new image enhancement scheme using wavelet transform, smooth and sharp approximation of a piecewise non linear filter technique after converting the RGB (Red, Green, and Blue) values of each pixel of the original image to HSV (Hue, Saturation, and Value). Wavelet transform is then applied to the luminance value of V component, it decomposes the input image into the four sub-bands by using Discrete Wavelet Transform (DWT).The low frequency sub-band is smoothened and the high frequency sub-bands are sharpened by using non linear piecewise filter. The inverse DWT to the smoothened low frequency sub-band and sharpened high frequency sub-bands. 1-level decomposition is used in the proposed system. The saturation components are enhanced by histogram equalization; the H components are not changed, if it changes in the H components could cause the color balance between the HSV components. The enhanced S and V combined with H are converted back to RGB values. The method has effectively achieved a successful enhancement of color images. The experimental result vividly displays the proposed algorithm is efficient enough to remove the noise resulting good enhancement.

Keywords
Color Image enhancement, RGB Color Space, Piecewise linear filter (PWL), HSV Color Space, Discrete Wavelet Transform.

1. INTRODUCTION
Enhancement plays a more vital factor in image processing; that is improving the quality of an image is named as enhancement. Enhancement can be made on both Gray scale and color images. Many algorithms have been described to enhance gray scale images. Recently, a image resolution enhancement technique using Discrete Wavelet Transform (DWT) for Satellite images, was reported by Demirel and Anbarjafari [1]. Interpolation in image processing is a method to increase the number of pixels in a digital image. Interpolation has been extensively used in many image processing applications[2],Meanwhile Homomorphic filtering, Low pass, and high pass filtering are the other techniques to work in spatial domain [3] and [4]. Later, these techniques were used for enhancing color images as well. Wu and su proposed an image resolution enhancement technique based on wavelet transform [5]. Since a fraction of the high-pass filtered image is added to the original data, the resulting effect produces edge enhancement and noise amplification as well. In order to address this issue, more effective approaches resort to nonlinear filtering that can realize a better compromise between image sharpening and noise attenuation [6]. Fabrizio Russo proposed enhancement system adopts a simple piecewise linear (PWL) function, in his algorithm only one piecewise linear (PWL) function to combine the smoothing and sharpening effects [7]. F. Russo and G. Ramponi proposed fuzzy systems are well suited to model the uncertainty that occurs when conflicting operations should be performed, (i.e.) detail sharpening and noise cancellation [8, 9]. S.Gopinath et.al was developed a piece wise linear (PWL) algorithm for a non linear filtering method of gray level images by using discrete wavelet Transforms [10]. Kaganami, et.al presented A color conversion method of color image Enhancement based on Hue Invariability with characteristics of human visual color consciousness in HSV color pattern [11]. The present work is based on the same procedure but deals with color images for improving the quality of images that are degraded by noise based on smooth approximation of piecewise linear (PWL) function. The proposed technique is presented in section 2 and the algorithm is given in section 3. Experimental results are discussed in section 4 and section 5 concludes the paper.

2. PROPOSED METHOD
The flow chart of the proposed method is shown in Figure.1. First, the given RGB noisy image is converted to HSV color space, after the luminance component (V) is decomposed by one level DWT. (Haar as wavelet function) It will decompose the original image into four frequency sub bands. Then, the noise in the frequency coefficients are reduced by smooth approximation of PWL filtering techniques. Finally, the enhanced V is obtained through the inverse wavelet transform, Adaptive histogram equalized S, and H are converted back to RGB enhanced image.

2.1 Input Image
The present work uses digital color images as the input image of size 512 x 512.

2.2 Color Conversion
The proposed method begins by Converting the RGB (Red, Green, and Blue) value of each pixel of any segment of the original image to HSV (Hue, Saturation, and Luminance) values [11]. The conversion is shown by the following equation (1).

$$H = Undefined \quad if\ MAX = MIN$$

$$H = 60 \times \frac{G-B}{MAX-MIN} + 0 \quad if \quad MAX = R \quad and \quad G \geq B$$

$$H = 60 \times \frac{G-B}{MAX-MIN} + 360 \quad if \quad MAX = R \quad and \quad G < B$$

$$H = 60 \times \frac{B-R}{MAX-MIN} + 120 \quad if \quad MAX = G$$

$$H = 60 \times \frac{B-R}{MAX-MIN} + 240 \quad if \quad MAX = B$$

$$S = \begin{cases} 0 & if \quad MAX = 0 \\ 1 - \frac{MIN}{MAX} & otherwise \end{cases}$$

$$V = MAX \tag{1}$$

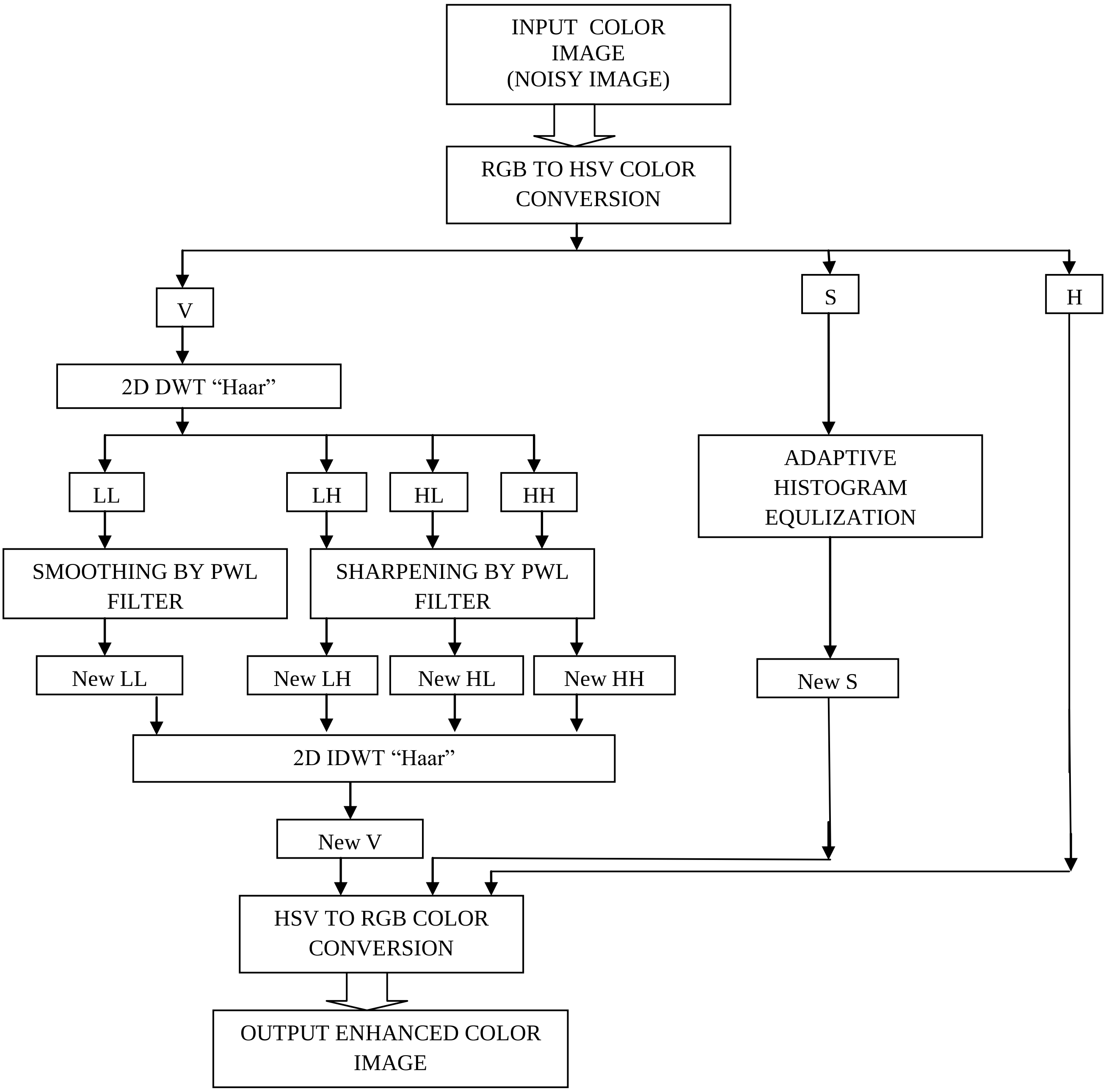


Figure. 1. Flow chart of Proposed Method

2.3 2-D Discrete Wavelet Transform (DWT)

Wavelets have been used quite frequently in image processing. Images can be represented both in terms of local spatial and frequency contents using wavelet transforms. The Fourier transform and DCT provides global frequency characteristics of an image, but they fail to provide local frequency characteristics. This drawback is overcome in wavelet transforms. A discrete wavelet transforms (DWT) for which the wavelets are discretely sampled for numerical analysis and functional analysis. This is overcome by DWT, it captures both frequency and time information. Discrete wavelet transform (DWT) decompose signals into sub-bands with smaller bandwidths and slower sample rates namely Low-Low (LL), Low-High (LH), High-Low (HL), and High-High (HH). With this, it is obtained four sub-bands from one level of transform – first lowpass sub-band having the coarse approximation of the source image called LL sub-band, and three high pass sub-bands that exploit image details across different directions – HL for horizontal, LH for vertical and HH for diagonal details. The 2-D wavelet decomposition of an image is performed by applying 1-D DWT along the rows of the image first, and, then, the results are decomposed along the columns. The luminance component (V) from HSV is used here for obtaining the wavelet transform. The frequency components of those sub-band images cover the frequency components of the luminance components value (V) is as shown in Fig. 2. Hence, discrete wavelet transform (DWT) is a suitable tool to be used for designing an image enhancement system.

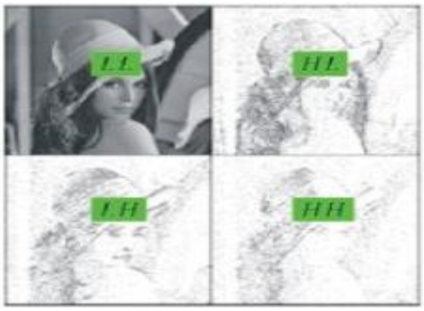


Figure. 2. Decomposition of V Component

2.3 PWL Filtering

Normally deal with digitized images having L gray levels. Let x(n) be the pixel luminance at location n = [n1, n2] in the input image. The enhancement algorithm operates on a 3 × 3 window around x(n). Let $x_1(n)$, $x_2(n)$, . . . , $x_N(n)$ briefly denote the group of N = 8 neighboring pixels, as shown in Figure 3 ($0 \le x(n) \le L-1$; $0 \le x_i(n) \le L-1$, i = 1, . . . , 8)

X_1(n)	X_2(n)	X_3(n)
X_4(n)	X(n)	X_5(n)
X_6(n)	X_7(n)	X_8(n)

Figure.3. 3 X 3 Window

Let y(n) represent the output of the enhancement system. F. Russo proposed enhancement system adopts a simple piecewise linear (PWL) Algorithm [7], is described by the following relationships:

$$y(n) = x(n) \oplus s(n) \tag{2}$$

$$S(n) = -\frac{1}{N}\sum_{i=1}^{N} h(\Delta x_i(n)) \tag{3}$$

$$\Delta x_i(n) = x(n) - x_i(n) \tag{4}$$

where symbol $\oplus$ represents the bounded sum a $\oplus$ b = min { a+ b , L − 1} and h is a PWL function whose behavior is controlled by two parameters k_{sm} and k_{sh}.

$$h(u) = \begin{cases} \frac{1}{2}k_{sh}u, & u < -4k_{sm}, \\ k_{sh}(u+2k_{sm}), & -4k_{sm} \le u < -2k_{sm}, \\ u+2k_{sm}, & -2k_{sm} \le u < -k_{sm}, \\ -u, & -k_{sm} \le u < k_{sm}, \\ u-2k_{sm}, & k_{sm} \le u < k_{sm}, \\ k_{sh}(u-2k_{sm}), & 2k_{sm} \le u < 4k_{sm}, \\ \frac{1}{2}k_{sh}u, & u \ge 4k_{sm}, \end{cases} \tag{5}$$

Equation (4) gives the luminance differences Δx_i between the central pixel and its neighbors. When these differences are small, the method performs smoothing, that is, an action that aims at reducing such differences in the enhanced image. Conversely, when the luminance differences are high, sharpening is provided, that is, an effect that tends to increase such differences. That gives the equation (5), as $|\Delta x_i|$ increases, its effect in equation (3) becomes quite different. More precisely, this effect is strong smoothing for very small differences ($|\Delta x_i(n)| < k_{sm}$), weak smoothing for small differences ($k_{sm} \le |\Delta x_i(n)| < 2k_{sm}$), strong sharpening for medium differences ($2k_{sm} \le |\Delta x_i(n)| < 4k_{sm}$), and weak sharpening for large differences ($|\Delta x_i(n)| \ge 4k_{sm}$). The shape of $h(u)$ has been designed to gradually combine the smoothing and sharpening effects. The choice of a 7-segment model is based on experimentation. It is a compromise between complexity and effectiveness. Models with more segments require more parameters and do not yield a significant improvement. On the other hand, models with less segments do not provide enough performance and flexibility. Now, the sharpening action is inroduced. If choose $k_{sh} > 0$ (typically $k_{sh} \le 6$), a sharpening effect is applied to the image pixels when $|\Delta x_i(n)| > 2k_{sm}$ in equation (5). Since sharpening can be considered as the opposite of the smoothing action [9, 10],it is set $h(\Delta x_i(n)) > 0$ when $\Delta x_i(n) > 2k_{sm}$ and $h(\Delta x_i(n)) < 0$ when $\Delta x_i(n) < -2k_{sm}$. In particular, this sharpening effect is stronger if $2k_{sm} \le |\Delta x_i(n)| < 4k_{sm}$ and weaker when $|\Delta x_i(n)| \ge 4k_{sm}$.

This choice aims at avoiding an annoying excess of sharpening along the object contours of the image.

2.4 Modified Enhancement Process

The quality of the enhanced image can be improved by introducing a further processing step for the cancellation of possible outliers still remaining in the image. If the image is corrupted by Gaussian noise, these outliers typically represent the fraction of noise located on the "tail" of the Gaussian distribution. Even if the probability of occurrence of these outliers is low, their presence can be rather annoying, especially in the uniform regions of the image. The processing scheme described by the equations (2) to (5) would require a large value of k_{sm} to smooth out this kind of noise and, as a consequence, some blurring of fine details could be produced. A more suitable choice is the adoption of an additional filtering step devoted to the cancellation of these outliers. This choice permits us to use a smaller value of k_{sm} that can satisfactorily preserve the image details. The filter for outlier removal adopts a different approach to process the luminance differences in the window. The filter is defined by the following relationship:

$$y(n) = x(n) - \underset{i=1,2,\ldots,N}{MIN}\{g(\Delta x_i(n)\} + \underset{i=1,2,\ldots,N}{MAX}\{g(-\Delta x_i(n)\} \quad (6)$$

Where g is a nonlinear function.

$$g(v) = \begin{cases} v, & 0 < v \le L-1, \\ 0, & v \le 0 \end{cases} \quad (7)$$

The shape of function g is chosen to achieve the exact correction in the ideal case of an outlier in a uniform neighborhood. As an example, let x(n) = a be a positive outlier and let $x_i(n) = b$ (i = 1, 2, . . . ,N) be the luminance values of the neighboring pixels (a > b). Since $\Delta x_i(n) = a - b > 0$, let $g(\Delta x_i(n)) = a - b$ and $g(-\Delta x_i(n)) = 0$. Thus equation (6) yields the exact value y(n) = b. The filtering action defined by the equations (6) and (7) can be applied after the sharpening process in order to remove outliers. A better choice, however, is to apply this filtering to the noisy input data before the enhancement process, thus avoiding amplification of these outliers.

3. ALGORITHM

BEGIN **ENHANCEMENT_ALGORITHM ()**

Step1: Initialization

Input: Noise Added Image(X)

Step 2
RGB to HSV color space conversion

Step 3:

Take V component and do Wavelet: Haar, Decompose the V component by Haar Wavelet Transform and store the sub-bands into LL, LH, HL, and HH arrays.

∀(***i,j***) of LL sub-band Call START_SMOOTHEN (LL,i,j)

∀ (***i,j***) of LH sub-band Call START_SHARPEN (LH,i,j)

∀ (***i,j***) of HL sub-band Call START _SHARPEN (HL,i,j)

∀ (***i,j***) of HH sub-band Call START _SHARPEN (HH,i,j)

Step 4:

Perform inverse Haar wavelet transform by using the modified sub-bands to get the enhanced V component.

Step 5:

Take S component and do Histogram equalization and get the enhanced S component.

Step 6:

HSV to RGB color space conversion and finally get the enhanced output image.

END **ENHANCEMENT_ALGORITHM ()**

BEGIN **START_SMOOTHEN (Low,i,j)**

(1) For every pixel (m,n) in *Wk*(*i,j*), call FIND_h(u);

(2) Find the minimum h(MIN) and maximum h(MAX) value.

(3) Term1 = MIN;

(4) Term2 = MAX;

(1) Low(i,j) = Low(i,j) - (Term1) + (-Term2);

(5) return

END **START_SMOOTHEN (Low,i,j)**

BEGIN **START_ SHARPEN (High,i,j)**

(1) For every pixel (m,n) in *Wk*(*i,j*), call FIND_h(u);

(2) Find the minimum h(MIN) and maximum h(MAX) value.

(3) Term3 = MIN;

(4) Term4 = MAX;

(1) High(i,j) = High(i,j) - (Term3) + (-Term4);

(5) return

END **START_ SHARPEN (High,i,j)**

BEGIN **FIND_ h(u)**

(1) Calculate the difference(D)between the pixels (m,n) and (i,j);

(2) Calculate h(u) for the Difference (D) by using PWL function equation (5)

(3) return;

END **FIND_h(u)**

.

4. EXPERIMENTAL RESULTS

To measure the performance of the proposed system, it is tested, the enhancement system with various images. The Gaussian noise is added to the original input image. Then proposed method for noise removal and enhancement is applied. The proposed method is compared with the image enhancement standard filters like Median, Unsharp, Laplacian and Gaussian filtering. The results are shown in Figure.4 for standard images and Figure.5 for color satellite images.

The RMSE is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. This is one of the most commonly used measures to measure the quality of the reconstruction. It is defined for the two images f(x,y) and $\hat{f}$(x,y) considering one of images as a noisy approximation of the other as follows

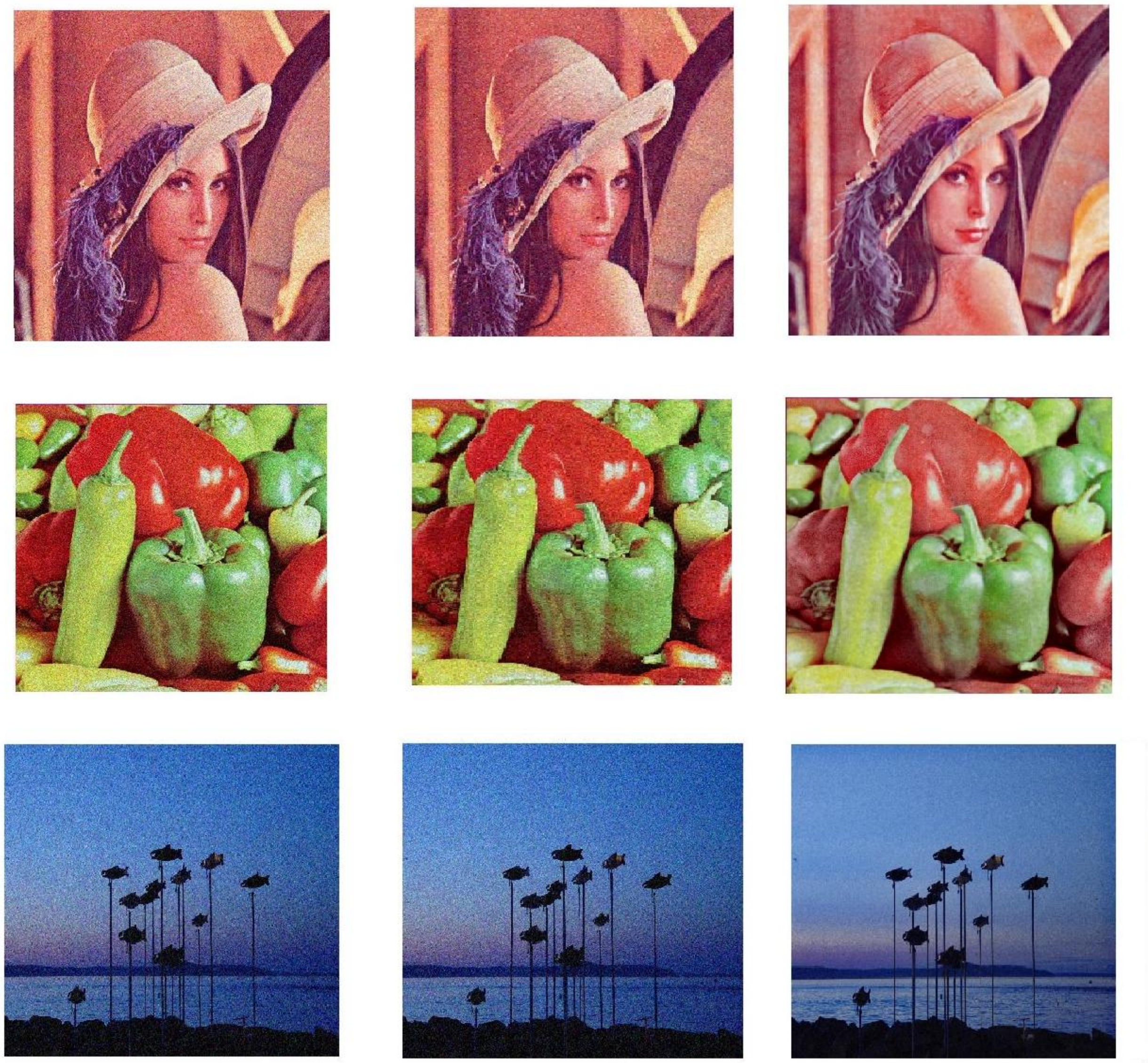
$$e_{rms} = \sqrt{\frac{1}{M}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left[\hat{f}(x,y) - f(x,y)\right]^2} = \sigma \quad (8)$$

The RMSE values of standard images and color satellite images for different methods are calculated and the comparative chart is shown Table 1and Table 3 respectively**.** From the tables it can be observed that the RMSE value of our proposed method is lower than the other methods.

PSNR, which is defined as

$$PSNR = 10\log_{10}\frac{(Peak\ \ to\ \ peak\ \ value\ \ of\ \ the\ \ referenced\ \ image)^2}{\sigma_s^2} \quad (9)$$

Peak to peak value of the referenced image is the maximum pixel value of the image. The peak signal to noise ratio is calculated from the error using the above formula. The higher the value of the PSNR, the better is the performance of that particular method. The PSNR values of standard images and color satellite images for different methods are calculated and the comparative values are shown in Table 2 and Table 4 respectively**.** From the tables, It is observed that the PSNR value of proposed method is higher than other methods.



(a) (b) (c)

Figure. 4. (a) Input image (b) Gaussian Filtering (c) Proposed Method

Table 1: Comparison of RMSE values for Standard color images by different filtering methods

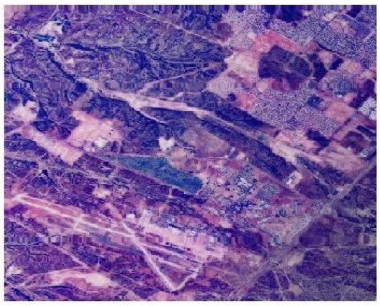
Standard Filters	Image		
	Lena	**Pepper**	**Fish**
Median filter	**140.5773**	**128.4133**	**111.5750**
Laplacian filter	**122.3151**	**112.6632**	**96.7357**
Unsharp filter	**83.9416**	**82.5190**	**82.7333**
Gaussian filter	**24.5172**	**24.2110**	**24.0558**
Proposed PWL Filter	**16.8929**	**21.0978**	**14.9993**

Table 2: PSNR values comparision of Standard color images by different Filtering methods

Standared Filters	Image		
	Lena (dB)	**Pepper (dB)**	**Fish (dB)**
Meadian filter	**5.1726**	**5.9587**	**7.1814**
Laplacian filter	**6.3817**	**7.0950**	**8.4191**
Unsharp filter	**9.6513**	**9.7997**	**9.7772**
Gaussian filter	**20.3414**	**20.4505**	**20.5064**
Proposed PWL Filter	**23.5767**	**21.6460**	**24.6093**





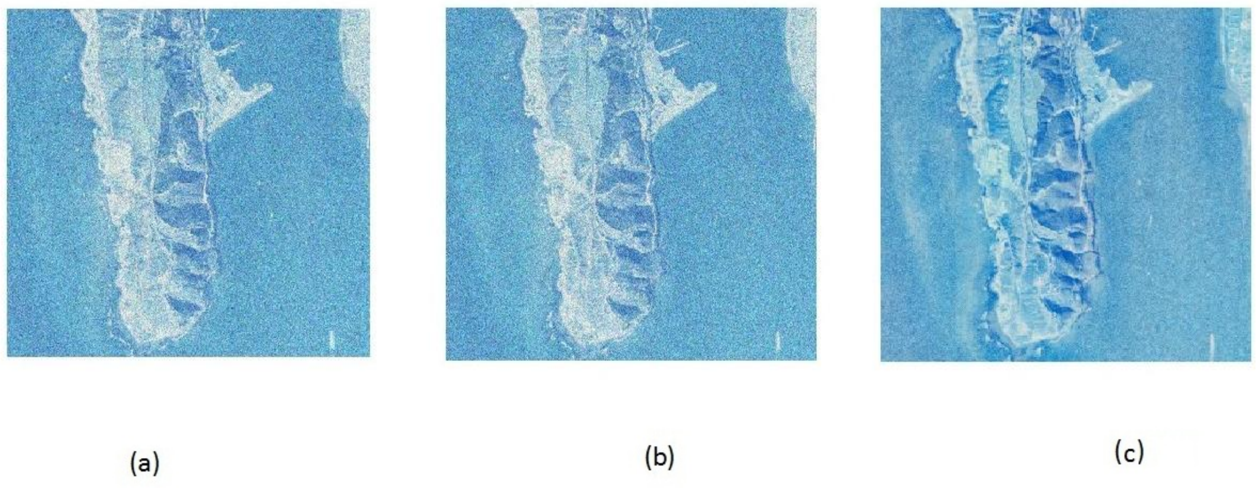


Figure. 5. (a) Input satellite image (b) Gaussian filtering (c) Proposed Method.

Table 3: Comparison of RMSE values for Satellite color images by different filtering methods.

Standard Filters	Image		
	Sat1	Sat2	Sat3
Median filter	146.4274	134.5102	171.0029
Laplacian filter	126.9606	116.8802	147.0952
Unsharp filter	84.2899	85.0799	84.5836
Gaussian filter	24.8285	24.9294	24.8256
Proposed PWL Filter	20.8748	18.4744	15.8939

Table 4: PSNR values comparision of Standard color images by different Filtering methods.

Standard Filters	Image		
	Sat1 (dB)	Sat2 (dB)	Sat3 (dB)
Median filter	4.8184	5.5556	3.4707
Laplacian filter	6.0574	6.7761	4.7787
Unsharp filter	9.6153	9.5343	9.5851
Gaussian filter	20.2318	20.1984	202328
Proposed PWL Filter	21.7383	22.7994	24.1061

5. CONCLUSION
This proposed algorithm gives to enhance color images using discrete wavelet transform and piece wise linear filtering (PWL). Quality of enhanced image obtain from the proposed algorithm is compared with other standard filters like Median, Unsharp, Laplacian and Gaussian filtering methods of image enhancement. The proposed image enhancement gives better RMSE and PSNR than other filtering methods. Future Scope, The Present work will be efficiently extended to Color Images and also for optimization with best suitable algorithm by making use of different Soft Computing techniques.

6. REFERENCES
[1] H.Demirel and G.Anbarjafari, Discrete Wavelet Transform-Based Satellite Image Resolution Enhancement, IEEE Trans. on Geoscience and Remote Sensing,Vol.49,No. 6, 1997-2000, Jun-2011.

[2] Y. Piao, I. Shin, and H. W. Park, "Image resolution enhancement using inter-subband correlation in wavelet domain," in *Proc. Int. Conf. Image Process.*, vol. 1, pp. I-445–448, 2007.

[3] J. S. Lim, "Two-Dimensional Signal and Image Processing", Englewood Cliffs, NJ: Prentice-Hall, 1990.

[4] R. C. Gonzales and E. Woods, "Digital Image Processing. Reading", MA: Addison-Wesley,1992.

[5] X. Wu, and B. Su, A Wavelet-based Image Resolution Enhancement Technique, Int. Conf on Electronics and Optoelectronics (ICEOE 2011), 2011, pp 62- 65.

[6] S. C. Matz and R. J. P. de Figueiredo, "A nonlinear technique for image contrast enhancement and sharpening," in *Proc. IEEE Int. Symp. Circuits and Systems (ISCAS '99)*, vol. 4 pp. 175–178, Orlando, Fla, USA, May–June 1999.

[7] Fabrizio Russo "Piecewise Linear Model-Based Image Enhancement," EURASIP , Journal on Applied Signal Processing, vol.12, pp. 1861–1869, 2004.

[8] F. Russo and G. Ramponi, "Fuzzy operator for sharpening of noisy images," *Electronics Letters*, vol. 28, no. 18, pp. 1715–1717, 1992.

[9] F. Russo and G. Ramponi, "Nonlinear fuzzy operators for image processing," *Signal Processing*, vol. 38, no. 3, pp. 429–440, 1994.

[10] S.Gopinathan and P.Thnagavel, "A Non Linear Technique for image enhancement based on Discrete wavelet Transform", European journal of Scientific Research, Vol.79, No.3, pp.328–336, 2012.

[11] H. G. Kaganami, Z. Beiji and M. S. Soliman, "Optimal Color Image Enhancement Using Wavelet and K-means Clustering",in IJDCT and Its Applications, Vol.5, No.1, pp 112-121, January-2011