Colored Satellites Image Enhancement Using Wavelet and Threshold Decomposition

Dr. Muna F. Al-Samaraie[1] and Dr. Nedhal Abdul Majied Al Saiyd[2]

1. Management Information System Department
Faculty of Economics and Administrative Sciences
Al-Zaytoonah University, Amman, Jordan

2. Computer Science Department
Faculty of Information Technology,
Applied Science University, Amman-Jordan

Abstract

For decades, several image enhancement techniques have been proposed. Although most techniques require profuse amount of advance and critical steps, the result for the perceive image are not as satisfied. In this study, we proposed a new method to enhance the satellite image which using intelligent aspect of filtering and describe multi-threshold technique with an additional step in order to obtain the perceived image. In this way, several simple filters can be combined to form a more efficient and more flexible context dependent filter. This paper proposes a new idea for edge enhancement using smoothing techniques. Various smoothing technologies are explored and implemented for comparing their performance with various threshold values.
Comparison is done by qualitative and quantitative approaches. From the results, specific filtering is only applied to the region for which it is suitable. We also evaluate the image quality. The proposed method shows dramatically increase in pixel distribution throughout the range of RGB. The result of this research is also beneficial in terms of geographical views due to the process which determined the difference appeared on each area.

Keywords: Image enhancement, sharpening, wavelet, threshold decomposition and satellite images.

1. Introduction

In the modern information system, digital images have been widely used in a growing number of applications. The effort on edge enhancement has been focused mostly on improving the visual perception of images that are unclear because of blur. In general, the popular edge enhancement filtering is carried out with the help of traditional filters [1, 2 and 3]. But these filters do have some problems, especially while enhancing a noisy image.

Noise removal and preservation of useful us information are important aspects of image enhancement. A wide variety of methods have been proposed to solve the edge preserving and noise removal problem. Recently, researchers have focused their attention on nonlinear smoothing techniques in the spatial domain. Most of these techniques are local smoothing filters, which replace the center pixel of the neighborhood by an average of selected neighbor pixels.
Mainly focusing on the clarity of the image and the number of computations done for enhancing the image, we developed a novel approach. The edge enhancement done by smoothing filters decreases the complexity and also increases the quality of the image [5]. The basic aim of edge enhancement is to modify the appearance of an image to make it visually more attractive or to improve the visibility of certain features specially the satellite images. The edge enhancement technique enhances all high spatial frequency detail in an image, including edges, lines and points of high gradients. In this approach, the details of edges in an image can be obtained by subtracting a smoothed image from the original [4]. This subtractive smoothing method has been used as the simplest way to obtain high spatial frequency image and this method of edge enhancement makes the image brighter and real edges are detected.
In spite of all these efforts, none of the proposed operators are fully satisfactory in real world applications. They do not lead to satisfactory results when used as a means of identifying locations at which to apply image sharpening. In this paper, the enhancement is applied through a framework of threshold decomposition. This has two advantages: it reduces the edge detection to a simple binary process; and it makes the estimation of edge direction straightforward. Edge detection and direction estimation may be carried out by identifying simple

patterns, which are closely related to the Prewitt operators [6].
The previous methods stated can work under certain circumstances; meanwhile, it is in accurate to use the method in case of low contrast image or low resolution image [12]. Another method was proposed lately on satellite image enhancement which proposed an additional step by enhancing the brightness of the image before working on edge detection. However, the process shows no statistical results in the research.
Therefore, the quality evaluation was still un-identical in order to compare the results. In this study we proposed a novel approach satellite image sharpening, we developed new algorithms in intensity evaluation and compare its quality with its original version. The processes were composed of image brightness, edge detection and the standard deviation of the image intensity performed by the Peak Signal to Noise Ratio (PSNR).
The structure of the paper is arranged as follows: section 1 included the introduction and section 2 included the methodology of the proposed scheme. The proposed method is explained with many details in Section 3. Section 4 included the results. Conclusions are shown in Section 5

2. Methodology

2.1 Image enhancement

Image enhancement is a process principally focuses on processing an image in such a way that the processed image is more suitable than the original one for the specific application. The word "specific" has significance. It gives a clue that the results of such an operation are highly application dependent. In other words, an image enhancement technique that works well for X-ray topographic images may not work well for satellite images.
The technique falls in two categories on the basis of the domain they are applied on. These are the *frequency* and *spatial* domains. The frequency domain methods works with the Fourier Transforms of the image. The term spatial domain refers to the whole of pixels of which an image is composed of. Spatial domain methods are procedures that operate directly on the pixels. The process can be expressed in Eq. (1):

$$g(x, y) = T[\, f(x, y)] \qquad (1)$$

Where $f(x, y)$ is the input image, $g(x, y)$ is the processed image, and T is an operator on f defined over some neighborhood of (x, y) [7]. A number of enhancement techniques exist in the spatial domain. Among these are histogram processing, enhancement using arithmetic, and logical operations and filters.
For the study of each and every filter, we have considered the following algorithms for implementation:

Mean Filter: Mean filtering is simply the process of replacing each pixel value in an image with the mean (average) value of its neighbors, including itself [4,11]. This is simply done using 3*3 kernel.

Median Filter: The median is calculated by first sorting all the pixel values from the surrounding neighborhood in numerical order and then replacing the pixel being considered with the middle pixel value [11]. This is also implemented using 3*3 kernels.

Mode Filter: Mode filtering simply involves the replacing of each pixel value in an image by the mode value of its neighbors, including itself [11]. This is also implemented by 3*3 kernels.

Circular Filter: Circular filter is implemented using the product of original matrix and convolution mask provided [11]. A 5*5 kernel is used here.

Pyramidal Filter: Pyramidal filter is implemented using the product of the original matrix and convolution mask provided [11]. A 5*5 kernel is used here.

Cone Filter: Cone filter is implemented using the product of original matrix and convolution mask provided [11]. A 5*5 kernel is used here.

2.2 Threshold Decomposition

Threshold decomposition is a powerful theoretical tool, which is used in nonlinear image analysis. Many filter techniques have been shown to 'commute with thresholding'. This means that the image may be decomposed into a series of binary levels, each of which may be processed separately. These binary levels can then be recombined to produce the final grayscale image with identical pixel values to those produced by grayscale processing. Hence a grayscale operation may be replaced by a series of equivalent binary operations.
The first threshold decomposition framework for image processing was introduced by [8]. This was capable of modeling a wide range of filters based on rank ordering such as the median. It was also capable of modeling linear finite impulse response (FIR) filters with positive weights. The framework was limited to modeling low pass filters or 'smoothers'. More recently the framework was modified by [9]. This modification introduced the ability to model

both linear and nonlinear filters with negative as well as positive filter weights. It in effect opened up the possibility to model high pass and band pass filters as well as low pass filters.

Motivated by this success an image sharpening technique is developed and implemented through a framework of threshold decomposition. Consider an integer-valued set of samples x_1, x_2, … , x_n forming the signal $X = (x_1, x_2, \ldots, x_n)$ where $x_i \in \{-m \ldots, -1, 0, 1, \ldots, m\}$. The threshold decomposition of X amounts to decomposing this signal into 2m binary signals $X^{-m+1}, \ldots, X^{0}, \ldots, X^{m}$, where the ith element of x^m is defined by the Eq. (2):

$$x_i^m = \begin{cases} 1 & \text{if } x_i \geq m \\ -1 & \text{if } x_i < m \end{cases} \quad (2)$$

The above threshold decomposition is reversible, such that if a set of threshold signals is given, each of the samples in X can be exactly reconstructed as shown in Eq. (3):

$$x_i = \frac{1}{2} \sum_{j=-m+1}^{m} x_i^j \quad (3)$$

Thus, an integer-valued discrete-time signal has a unique threshold signal representation, and vice versa.

2.3 Image Sharpening

The principle for image filtering method and edge detection can be done by several techniques. Firstly, signal reduction is required to emphasize the edge and brighten the image. In this case, high pass filter is used to filter the signal as well as to detect the edges from the original image. Hence, the solution for this process is the total of the original image and the edge as the Eq. (4):

$$f_s(x_i, y_i) = f(x_i, y_i) + \Omega F(f(x_i + y_i)) \quad (4)$$

Where:
$f(x_i,y_i)$ = The original pixel value at the coordinate (x_i,y_i)
$F(.)$ = The high pass filter
Ω = A tuning parameter which is greater or equal to zero
$f_s(x_i,y_i)$ = The sharpened pixel at the coordinate (x_i,y_i)

The value represents Ω as the perspective degree of sharpness, the higher the Ω the more sharpened is the image. Another well known technique which enhances blur images is called Unsharp Masking (UM) technique. The solution of this technique begins by subtracting the original image with the blur image. In the other words, subtract low pass filter from the input image. These results for the output image which emphasizes on the detail and sharpness [10]. Generally, blurred images occur by several low pass filtering in the image. Hereby was the Eq. (5) for Unsharp Masking technique:

$$f_s(x_i, y_i) = f(x_i, y_i) - f_b(x_i, y_i) \quad (5)$$

Where:
$f_s(x,y)$ = The sharpened image obtained by unsharp masking
$f_b(x,y)$ = The blurred version of $f(x_i,y_i)$

According to this equation, increase in sharpness is eligible by using high boost filter [11]. The relations between the above two equations were as shown in Eq. (6)

$$f_{sh}(x_i, y_i) = A * f(x_i, y_i) - f_b(x_i, y_i)$$

or:

$$f_{sh}(x_i, y_i) = (A-1) + f_h(x_i, y_i) \quad (6)$$

A = A variable which is greater or equal to 1
$f_{sh}(x_i,y_i)$ = The high boost sharpened image
$f_b(x_i,y_i)$ = The low pass filter of $f(x_i,y_i)$
$f_h(x_i,y_i)$ = The high pass filter of $f(x_i,y_i)$

2.4 The Discrete Wavelet Transform

The generic form for a one-dimensional (1-D) wavelet transform is shown in Figure (1). Here a signal is passed through a lowpass and highpass filter, *h* and g, respectively, then down sampled by a factor of two, constituting one level of transform. Multiple levels or “scales” of the wavelet transform are made by repeating the filtering and decimation process on the lowpass branch outputs only. The process is typically carried out for a finite number of levels K, and the resulting coefficients, $d_{i1}(n)$, $i \in \{1,\ldots,K\}$ and $d_{K0}(n)$, are called wavelet coefficients.

Only the maximally decimated form of the wavelet transform is used, where the downsampling factor in the decomposition and upsampling factor in the reconstruction equals the number of filters at each level (namely two).

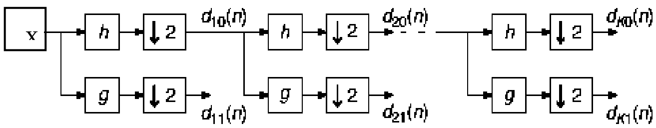


Figure 1: A K-level, 1-D wavelet decomposition. The coefficient notation $d_{ij}(n)$ refers to the jth frequency band (0 for low and 1for high) of the ith level of the decomposition.

Referring to Figure (1), half of the output is obtained by filtering the input with filter H(z) and down-sampling by a factor of two, while the other half of the output is obtained by filtering the input with filter G(z) and down-sampling by a factor of two again. H(z) is a low pass filter, while filter G(z) is a high pass filter.
The 1-D wavelet transform can be extended to a two-dimensional (2-D) wavelet transform using separable wavelet filters. With separable filters the 2-D transform can be computed by applying a 1-D transform to all the rows of the input, and then repeating on all of the columns. Using the Lena image in Figure (2a) shows an example of a one-level *(K =1)*, 2-D wavelet transform, The example is repeated for a two-level *(K=2)* wavelet expansion in Figure (2b).
In two dimensions, usually apply filtering both horizontally and vertically. Filtering in one-direction results in decomposing the image into two "components". The total numbers of produced "components" after the vertical and horizontal decompositions is four. These 4-components are referred to as image subbands, LL, HL, LH, HH. The first subband (the LL subband) will contain low pass information, which is essentially a low-resolution version of the image. Subband HL will contain low pass information vertically and high pass information horizontally, and subband LH will contain low pass information horizontally and high pass information vertically. Finally, subband HH will contain high pass information in both directions [13].
From Figure (2a) subband LL is more important than the other 3 subbands, as it represents a coarse version of the original image. The multiresolutional features of the wavelet transform have contributed to its popularity.

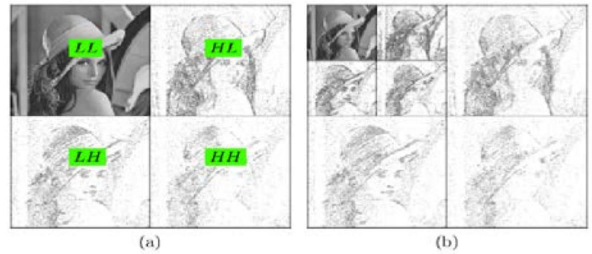


Figure 2: (a) One level wavelet transform in both directions of a 2D signal. (b) Two levels of wavelet transform in both directions.

3. The Proposed Scheme

3.1 Sub-band Coding

Sub-band coding is a coding strategy that tries to isolate different characteristics of a signal in a way that collects the signal energy into few components. This is referred to as energy compaction. Energy compaction is desirable because it is easier to efficiently code these components than the signal itself [16].
The sub-band coding scheme tries to achieve energy compaction by filtering a signal with filters of different characteristics. By choosing two filters that are orthogonal to each other and decimating the output of these filters a new two component representation is achieved as shown in Figure (3). In this new representation, hopefully, most of the signal energy will be located in either **a** or **d**.

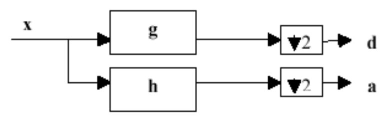


Figure 3: Splitting of the signal x into two parts.

The filters **h** and **g** are usually low-pass and high-pass filters as mentioned previously. The two components **a** and **d** will then be a low-pass and a high-pass version of the signal x. Images have a typical low-pass characteristics, and this is the reason why we should expect **a** to contain most of the energy if **x** is an image.
Besides trying to achieve energy compaction the filters **h** and **g** should be chosen so that perfect reconstruction of **x** from **a** and **d** is possible. In Figure (3) a two-component representation of **x** is achieved. It might be desirable to divide the signal into more components. A more common choice however is to cascade the structure in Figure (3). There are two major strategies for cascading the filters, the hierarchical structure and the flat structure. In the hierarchical structure the output from the low-pass filter is treated as the input to a new filter pair as depicted in Figure (4). While in the flat structure both the low-pass and the high-pass outputs are inputs to a filter pair, this structure is depicted in Figure (5). In both figures the corresponding splitting of the frequency axis is also shown. The process of dividing the signal into components will be referred to as decomposition or transform.

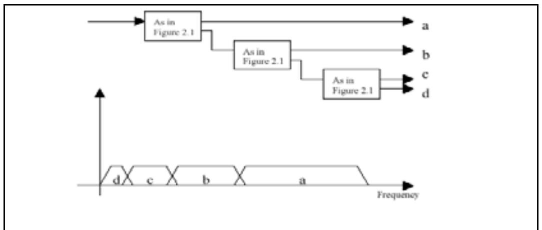


Figure 4: The hierarchical filter structure

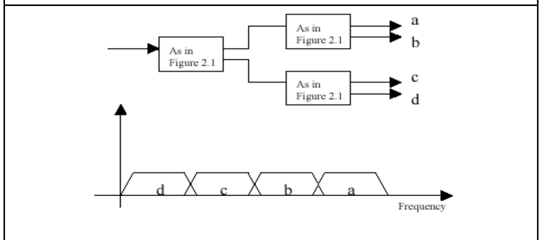


Figure 5: The flat filter structure

3.2 Extension to More Dimensions

To be able to use sub-band coding for images, the scheme above has to be adapted to two-dimensional signals. The extension of the sub-band coding scheme to higher dimension is straight-forward. Apply the filters repeatedly to successive dimensions. For a NxN image, first compute N one-dimensional transforms corresponding to transforming each row of the image as an individual one-dimensional signal. This will result in 2 NxM sub-images, one corresponding to the low-pass filtered rows and one corresponding to the high-pass filtered rows. Each of these sub-images is then filtered along the columns splitting the data into 4 MxM sub-images (low-pass row low-pass column, low-pass row high-pass column, high-pass row low-pass column, high-pass row high-pass column). This completes the one stage of the decomposition of an image. The process is depicted in Figure (6).

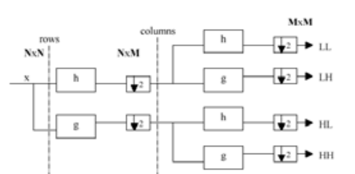


Figure 6: One stage of a two-dimensional decomposition

3.3 Wavelet Packets

The concept of wavelet packets (WP) extends the octave-band tree structured filter bank to consist of all possible frequency splits, so that best decomposition topology can be chosen to suit the individuality of different images. Figure (7) shows all of the possible representations of a wavelet packet decomposition of maximum depth two, among which the full tree is at the first position from left.

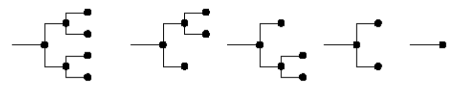
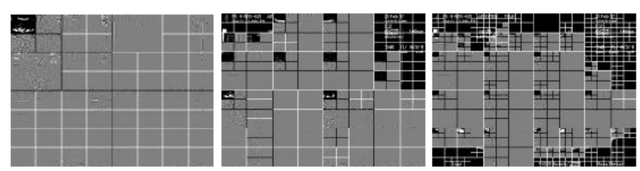


Figure 7: Possible wavelet packet trees, maximum depth=2

The best basis subtree is chosen among the entire library of wavelet packet bases. The problem of bit allocation for the decomposed subbands at a target bit rate is concerned with a set of given admissible quantization choices.
Each decomposition divides an image into four quadrants. Two-dimensional frequency partition produces four subbands: LL, LH, HL and HH. General space-frequency segmentation applies the general time-frequency-pruning algorithm to choose between the four-way splits in space or frequency in a space-frequency tree. This algorithm should generate a better optimal basis than both the single-tree and the double-tree. Its basis must be at least as good as the best double-tree/single-tree basis, because the set of possible double-tree/single-tree bases is a subset of the possible SFS bases.
An example for this partition is shown in Figure (8). It has maximum decomposition depth of five. The white lines indicate that the sub-image is space split, while the black lines indicate that frequency segmentation is applied. If there is no line inside the sub-image, this will indicate that there is no splitting performed on the sub-image.



level=3 level=4 level=5

Figure 8: partitions

The adaptive partitioning is done as follows:

1. Decompose an image component into blocks of fixed size (say 128 or 64).
2. If the size of the considered subblock is greater than MinSiz then this subblock must be tested to determine whether it requires further partitioning or not.
3. Initial subblocks will be partitioned, either as spatial (space) partitioning or as frequency (DWT) partitioning.
4. The Median Adaptive Predictor (MED) is utilized to evaluate whether the partitioning is performed in space or frequency.
5. There is one parameters have a great effects on selecting an appropriate partitioning types (the threshold). This operation is performed after doing the space and frequency partitioning on the same block, and then selecting partitioning type whose

error is less than other and it is higher than a selected threshold.

6. According to these conditions, the partitioning operation is done on all the image block. These operations continue until the block size reaches the MinSiz or they are uniform and the error of MED predictor doesn't exceed the threshold value.
7. the algorithm of partitioning as follows

```
1)initialization: /* Wid & Hgt are the width
and height of image */
   Nx=Wid div MaxSiz; Ny=Hgt div MaxSiz; L=0;
   Input Rat and Thr by the user
2) for each (Iy,Ix) where Iy=0 to Ny-1 :
Ys=Iy*MaxSiz; and Ix=0 to Nx-1: Xs=Ix*MaxSiz;
do:
     2.1) read all the fields of initialized
partitions:
          Part[L].X=Xs; Part[L].Y=Ys;
Part[L].Siz=MaxSiz;
Part[L].Typ=0; Part[L].Nxt=L+1;
     2.2) increment L by 1
   end for each
3) put –1 at the last field Nxt of the last
  partition
4) compute the minimum size:
  MinSiz=MaxSiz/2^levels;
5) initialize J=0;
6) repeat the flowing operations:
     if Part[J].Siz>MinSiz then put the
  coefficients in A[]
6.1) Send A[] to the MED of space with its size
  and return the Error E1
       6.2) Apply wavelet transformation A[]
  and return B[]
6.3) Send B[] to the MED of frequency with its
  size and return the Error E2
6.4) if (E1>Thr) or (E2>Thr)
if  (E1<=Rat*E2)  then  partition  the  block  with
  space segmentation
else partition the block after applying DWT
     else J=part[j].nxt
if J not equal -1 then goto step 6
     else exit
```

The algorithm of smoothing is as follows:

- A block (space partitioning) which is homogeneous is to be filtered by the moving of mean filter.
- A block (frequency partitioning) which has relative weak edges or un-continued edges, are filtered by the mode filter.
- A block (reminder) which has sharp edges is to be filtered by the median filter.

The following figure shows the proposed scheme:

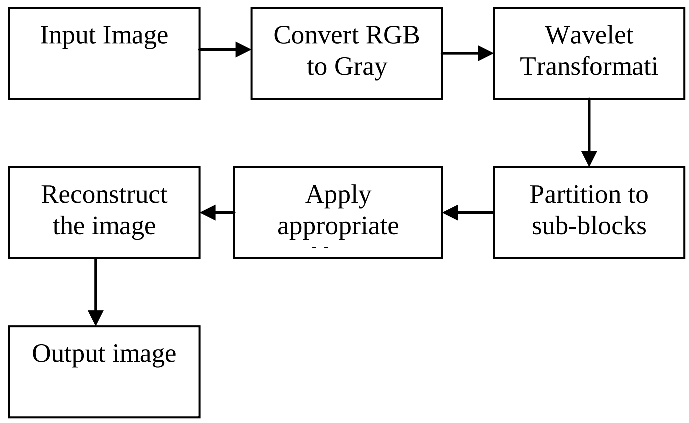


Figure 9: The Proposed Scheme

3.4 Image quality evaluation

The result image can be evaluated with two characteristics, distortion and sharpness. According to the distortion evaluation, adjusting errors are required, by computing the Mean Square Error (MSE). Mean square error has been the performance metric in lost performance. Peak Signal to Noise Ratio (PSNR) adjusts the quality of the image which the higher the PSNR refers to the better quality is the image [11]. The formula for MSE and PSNR are Eq. (7) and Eq. (8)

$$MSE = \frac{\sum_{MN}[I_1(m,n)-I_2(m,n)]^2}{M.N} \quad (7)$$

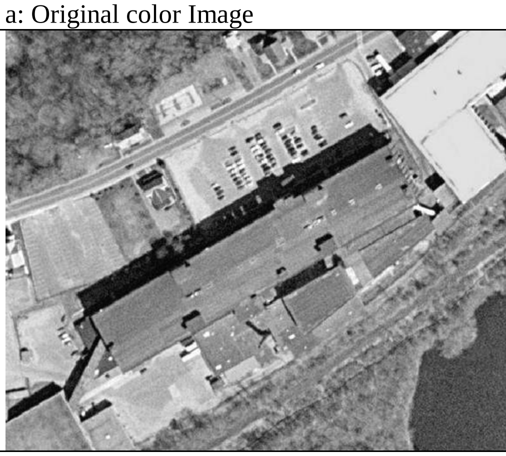
$$PSNR = 10\log_{10}\left[\frac{R^2}{MSE}\right] \quad (8)$$

The MSE expression is generally referred to the absolute error equation because the former error is analytically tractable. The most common error in image processing is the normalized brightness of the image. In the previous equation, M and N are the number of rows and columns of the input image, respectively. Then, all the blocks would compute the PSNR. In the PSNR equation, R is the maximum fluctuation in the input image data type.

4. Results

This section presents application results for the enhancement of satellite images. The images tested in the research were performed shown in Figure 10 and 11which was express in the numerical form of satellite image.

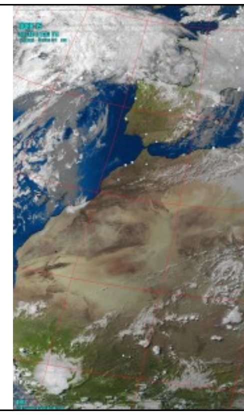
a: Original color Image



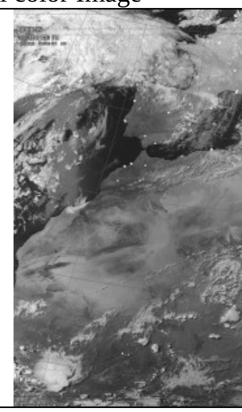
b: Gray Scale image

c: Enhanced Image

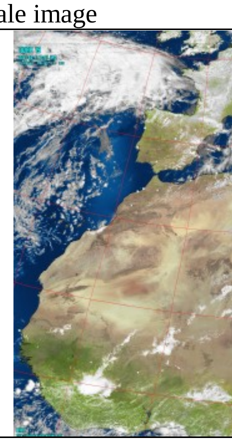
Figure 10: The Enhanced Image



A: Original color Image



b: Gray Scale image



c: Enhanced Image

Figure 11: The Enhanced Image

In order to compare the results accurately, Figure 10 and 11 represents the final step which includes subtracting the edge detected image from the original image. As a consequence, the MSE of the output image and the input image values at 0.63 and 0.49, respectively. In this study, we determined the total difference by comparing the PSNR between the original image and the output image, which the PSNR values at 25.67 and 28.95 dB, respectively.

Practically, the PSNR which values higher than 30 dB is invisible for human sight to analyze the color distortion between two images. The experimental result with the new algorithm procedure shown in figure10 and 11. Figure (a) is the original image and figure (b) is the result of color to grayscale transformation and finally, figure (c) show the result of the enhanced.

5. Conclusions

This paper introduced a new enhancement filter for digital satellite images. In the proposed scheme, the edge detected guided smoothing filters succeeded in enhancing low satellite images. This was done by accurately detecting the positions of the edges through threshold decomposition. The detected edges were then sharpened by applying smoothing filter. By utilizing the detected edges, the scheme was capable to effectively sharpening fine details whilst retaining image integrity. The visual examples shown have demonstrated that the proposed method was significantly better than many other well-known sharpener-type filters in respect of edge and fine detail restoration.

6. References

[1] Nick Kanopoulos, Nagesh Vasanthvada and Robert L Baker, "Design of an Image Edge Detection Filter Using the Sobel Operator", IEEE Journal of Solid-State Circuits, (1988), Vol. 23, No. 2, pp. 358-367.

[2] Bin Wang D, Rose M and Aly A Farag, "Local Estimation of Gaussian-Based Edge Enhancement Filters Using Fourier Analysis", IEEE Transactions on Acoustics, Speech, and Signal Processing, (1993), Vol. 5, pp. 13-16.

[3] Day-Fann Shen, Chui-Wen Chiu and Pon-Jay Huang, "Modified Laplacian Filter and Intensity Correction Technique for Image Resolution Enhancement", IEEE International Conference on Multimedia and Expo, (2006), Vol. 7, Nos. 9-12, pp. 457-460.

[4] Cheevasuvit F, Dejhan K and Somboonkaew A "Edge Enhancement Using Transform of Subtracted Smoothing Image", ACRS, (1992), Vol. 3, No. 12, pp. 23-28

[5] Jin Jesse S "An Adaptive Algorithm for Edge Detection", MVA'SO IAPR Workshop on Machine Vision Applications, (1990), Vol. 9, November 28-30, pp. 14-17.

[6] J. M. Prewitt, 1970, "Object enhancement and extraction," Picture Processing and Psychopictorics, pp. 75-149.

[7] D.Stark and W.Bradley Jr., Ed. 1992, Magnetic Resonance Imaging, St. Louis, MO: Mosby.

[8] J. P. Fitch, E. J. Coyle, and N. C. Gallagher, "Median filtering by threshold decomposition," IEEE Transactions on Acoustics, Speech and Signal Processing, 1984, vol. 32, pp. 1183-1188.

[9] G. R. Arce, "A general weighted median filter structure admitting negative weights," IEEE Transactions on Signal Processing, 1998, vol. 46, pp. 3195-3205.

[10] Xu, D. and R. Wang, 2009. An improved FoE model for image deblurring. Int. J. Comput. Vis., 81: 167-171. DOI: 10.1007/s11263-008-0155-3

[11] Gonzales, R.C. and R.E. Woods, 2002. Digital Image Processing. 2nd Edn., Prentice Hall, USA., ISBN: 10: 0130946508, pp: 793.

[12] Chen, Z.Y., B.R. Abidi, D.L. Page and M.A. Abidi, 2006. Gray Level Grouping (GLG): An automatic method for optimized image contrast enhancement-Part I: The basic method. IEEE Trans. Image Process., 15: 2290-2302. DOI: 10.1109/TIP.2006.875204

[13] C.A. Christopoulos, T. Ebrahimi and A.N. Skodras. "JPEG2000: The New Still Picture Compression Standard", Media Lab, Ericsson Research, Ericsson Radio Systems AB, S-16480 Stockholm, Sweden. http://www.eecs.harvard.edu/~michaelm/CS222/jpegb.pdf

Dr. Muna F. Al-sammarai. She obtained her B.Sc. degree from Al-Mansour University Baghdad-Iraq in 1992, M.Sc. form University of Baghdad and PhD degrees from University of Technology, Baghdad-Iraq in 1997 and 2002 respectively. She is an Assistant Prof. at MIS Dept., Faculty of Faculty of Economics and Administrative Sciences in Al-Zaytoonah University, Amman, Jordan. Her research interests include: Software Engineering, Image Processing, and Intelligent Systems.

Dr. Nedhal A. Al-Saiyd. She got her B.Sc. degree from University of Mosul-Iraq in 1981, M.Sc. and PhD degrees from University of Technology, Baghdad-Iraq in 1989 and 2000 respectively. She is an Assistant Prof. at Computer Science Dept., Faculty of Information Technology, in the Applied Science University, Amman, Jordan. Her research interests include: Software Engineering, Ontology Engineering, Intelligent Systems, User Authentication, e-learning and Speech Processing.