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Development of Algorithms for Contrast Enhancement of Remote Sensing Images

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Abstract— **For many years remote sensing images have played an important role in almost all fields such as meteorology, agriculture, geology, education etc. As the rising demand for high quality remote sensing images, contrast enhancement techniques are required for better visual perception and color reproduction. In this paper we explained some new enhancement techniques which use dominant brightness level analysis and adaptive intensity transformation with discrete wavelet transform and dual tree complex wavelet transform, DTCWT with principal component analysis (PCA), and a mathematical method for knee correction. Although various histogram equalization methods are proposed in the literature. They tend to degrade the overall image quality by exhibiting saturation artifacts in both low- and high- intensity layers. The proposed algorithms overcome this problem. In one method the DWT is performed first and then decompose the LL subband into low- middle-high- intensity layers using log-average luminance. Intensity layer transfer functions are adaptively estimated by using knee transfer function and the gamma adjustment function based on dominant brightness level on each layer .After the intensity transformation the enhance image is get back by taking Inverse DWT. We can do the decomposition using DTCWT in second method for better result. The contrast enhancement is performed with PCA and alternate knee correction method along with DWT and DTCWT for better results. The performance of every method is evaluated with parameters such Mean Square Error (MSE), Measure of Enhancement (EME), Peak Signal to Noise Ratio (PSNR) and Mean Absolute Error (MAE).**

Index Terms— **Adaptive intensity transfer function, contrast enhancement, discrete wavelet transform (DWT), dominant brightness level analysis, dual tree complex wavelet transform (DTCWT), remote sensing.**

I. .INTRODUCTION

Image enhancement techniques improve the quality of an image as perceived by a human. The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide better input for other automated image processing techniques. These techniques are most useful because many satellite images when examined on a colour display give inadequate information for image interpretation. There is no conscious effort to improve the fidelity of the image with regard to some ideal form of the image. There exists a wide variety of techniques for improving image quality. The contrast stretch, density slicing, edge enhancement, and spatial filtering are the more commonly used techniques. Image enhancement is attempted after the image is corrected for geometric and radiometric distortions. The proposed paper introduces some new methods for contrast enhancement.

Histogram equalization (HE) [1] has been the most popular approach to enhancing the contrast in various application areas such as medical image processing, object tracking, speech recognition, etc. HE-based methods cannot, however, maintain average brightness level, which may result in either under- or oversaturation in the processed image. For overcoming these problems, bi-histogram equalization (BHE) [2] method have been proposed by using decomposition of two subhistograms. For further improvement, the recursive mean-separate HE (RMSHE) [3] method iteratively performs the BHE and produces separately equalized subhistograms. However, the optimal contrast enhancement cannot be achieved since iterations converge to null processing. And also proposed a modified HE method which is based on the singular-value decomposition of the LL subband of the discrete wavelet transform (DWT) [4] [5] . In spite of the improved contrast of the image, this method tends to distort image details in low- and high-intensity regions.

In remote sensing images, the common artifacts caused by existing contrast enhancement methods, such as drifting brightness, saturation, and distorted details; need to be minimized because pieces of important information are widespread throughout the image in the sense of both spatial locations and intensity levels. For this reason, enhancement algorithms for satellite images not only improve the contrast but also minimize pixel distortion in the low- and high-intensity regions.

For achieving this goal we presented three new methods which uses adaptive intensity transfer function [6], alternate knee correction and principal component analysis along with DWT [7] and DTCWT [8] for comparative study.

II. IMAGE DECOMPOSITION TECHNIQUES

For the given three new methods we have to first perform either DWT or DTCWT for image decomposition. The theories behind the two are given in the following paragraphs.

A. Discrete Wavelet Transform (DWT)

An image is represented as a two dimensional array of coefficients, each coefficient representing the brightness level in that point. When looking from a higher perspective, the coefficients cannot be differentiated as more important one, and lesser important one. But most natural images have smooth colour variations, with the fine details being represented as sharp edges in between the smooth variations.

Technically, the smooth variations in colour can be termed as low frequency variations and the sharp variations as high frequency variations. The low frequency components constitute the base of an image and the high frequency components add upon them to refine the image thereby giving a detailed image. Hence the smooth variations are demanding more importance than the details. Separating the smooth variations and details of the image can be done in many ways. One such way is the decomposition of the image using Discrete Wavelet Transform (DWT)

DWT decomposes an image into four sub-bands: approximation and detailed sub-bands- horizontal, vertical, and diagonal. The detailed sub-bands shows variations along the columns (horizontal edges), rows (vertical edges), and diagonals (diagonal edges) respectively As shown in Fig. 1 at each level, approximation sub-band is decomposed into the above mentioned four sub-bands. A low pass filter and a high pass filter are chosen, such that they exactly have the frequency range between themselves. The filter pair is called the analysis filter pair. First the low pass filter is applied for each row of data, thereby getting the low frequency components of the row. Now the high pass filter is applied for the same row of data, and similarly the high pass components are separated and placed by the side of the low pass components. This procedure is done for all rows. Next, the filtering is done for each column of the intermediate data. The resulting two dimensional arrays of coefficients contain four bands of data, each labeled as LL (low- Low), HL (high-low), LH (Low-High) and HH (High-High). The LL band can be decomposed once again in the same manner, thereby producing even more subbands. This can be done up to any level, thereby resulting in a pyramidal decomposition as shown in Fig.1. The LL band at the highest level can be classified as most important and the other detail bands can be classified as of lesser importance, with the degree of importance decreasing from the top of the pyramid to the bands at the bottom. In Fig. 1 three level decomposition is shown. Here, L & H represents low frequency and high frequency components respectively. The sub-band LL denotes the low frequency component of the image, which is the approximation sub-band of the original image. The sub-band HL is the low frequency component in horizontal direction and the high frequency component in vertical direction, which shows the horizontal edge in the original image. The sub-band LH is the high frequency component in horizontal direction and the low frequency component in vertical direction, which shows the vertical edge in the original image. The sub-band HH is the high frequency component, which manifests the diagonal edges in the original image.

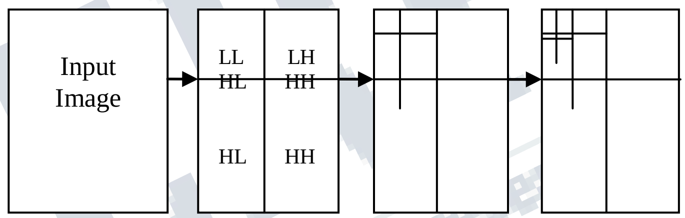

Fig. 1. Flow chart of the DWT decomposition

B. Dual tree complex wavelet transform (DTCWT)

There mainly some problems associated with DWT such as oscillations, shift variance, aliasing and lack of directionality. All these problems can be removed in DTCWT.

The dual tree approach, which is based on two filter banks and two bases is shown in Fig. 2.

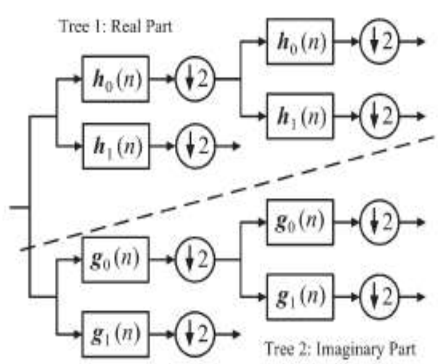

Fig. 2. 2 Level 1D DTCWT

The idea behind the dual-tree approach is quite simple. The dual tree CWT employs two real DWTs; the first DWT gives the real part of the transform while the second DWT gives the imaginary part. The decomposition image is shown in Fig 2 and it its reverse will give final result. The two real wavelet transforms use two different sets of filters. The two sets of filters are jointly designed so that the overall transform is approximately analytic. Let $h_0(n),\ h_1(n)$ denote the low-pass/high-pass filter pair for the upper FB, and let $g_0(n),\ g_1(n)$ denote the low-pass/high-pass filter pair for the lower FB. We denote the two real wavelets associated with each of the two real wavelet transforms as $\varphi_h(t)$ and $\varphi_g(t)$. To invert the transform, the real part and the imaginary part are each inverted the inverse of each of the two real DWTs are used to obtain two real signals. These two real signals are then averaged to obtain the final output. Note that the original signal x (n) can be recovered from either the real part or the imaginary part alone. DT-CWT produces six directional subbands, oriented at $\pm 15^0$, $\pm 45^0$ and$\pm 75^0$, while the DWT produces only three directional subbands, oriented at 0^0 , 45^0 and90^0 .

III. ALGORITHM 1-CONTRAST ENHANCEMENT USING DOMINANT BRIGHTNESS LEVEL ANALYSIS AND ADAPTIVE INTENSITY TRANSFORMATION

In this section present a novel contrast enhancement algorithm for remote sensing images using dominant brightness level-based adaptive intensity transformation as shown in Fig.3.We can use DWT or DTCWT for image decomposition. This decomposes the input image into wavelet subbands and decomposes the LL subband into low, middle, and high-intensity layers by analyzing the log-average luminance of the corresponding layer. The adaptive intensity transfer functions are computed by combining the knee transfer function [9] and the gamma adjustment function [10] [11]. All the contrast enhanced layers are fused with an appropriate smoothing, and the processed LL band undergoes inverse transform together with unprocessed LH, HL, and HH subbands to reconstruct the finally enhanced image.

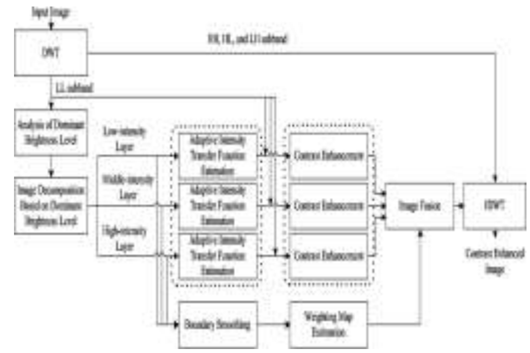

Fig.3: Block diagram of Algorithm 1

A. Analysis of Dominant Brightness Levels

If we do not consider spatially varying intensity distributions, the correspondingly contrast enhanced images may have intensity distortion and lose image details in some regions. For overcoming these problems, first decompose the input image into multiple layers of single dominant brightness levels. To use the low-frequency luminance components, perform the DWT on the input remote sensing image and then estimate the dominant brightness level using the log average luminance in the LL subband. Since high-intensity values are dominant in the bright region, and vice versa, the dominant brightness [12] [13] at the position (x, y) is computed as,

$$D(x, y) = \exp\left(\frac{1}{N_L}\sum_{(x,y)\varepsilon S}\{logL(x,y) + \varepsilon\}\right) \qquad (1)$$

Where S represents a rectangular region encompassing (x, y), L(x, y) represents the pixel intensity at (x, y), N_L represents the total number of pixels in S, and ε represents a sufficiently small constant that prevents the log function from diverging to negative infinity. The low-intensity layer has the dominant brightness lower than the pre specified low bound. The high intensity layer is determined in the similar manner with the pre specified high bound, and the middle-intensity layer has the dominant brightness in between low and high bounds. The normalized dominant brightness varies from zero to one, and it is practically in the range between 0.5 and 0.6 in most images. For safely including the practical range of dominant brightness, we used 0.4 and 0.7 for the low and high bounds, respectively.

B. Edge Preserving Contrast Enhancement Using Adaptive Intensity Transformation

Based on the dominant brightness in each decomposed layer, the adaptive intensity transfer function is generated. Since remote sensing images have spatially varying intensity distributions, we estimate the optimal transfer function in each brightness range for adaptive contrast enhancement. The adaptive transfer function is estimated by using the knee transfer and the gamma adjustment functions. For the global contrast enhancement, the knee transfer function stretches the low-intensity range by determining knee points according to the dominant brightness of each layer. More specifically, in the low-intensity layer, a single knee point is computed as,

$$P_l = b_l + w_l\ (b_l - m_l) \qquad (2)$$

Where b_l represents the low bound, w_l represents the tuning parameter, and m_l represents the mean of brightness in the low intensity layer. For the high-intensity layer, the corresponding knee point is computed as,

$$P_h = b_h - w_h\ (b_h - m_h) \qquad (3)$$

Where b_h represents the high bound, w_h represents the tuning parameter, and m_h represents the mean of brightness in the low intensity layer. In the middle intensity layer, two knee points are computed as,

$$P_{ml} = b_l - w_m(b_{ml} - m_m) + (p_l - p_h) \qquad (4)$$

$$P_{mh} = b_h + w_m(b_{mh} - m_m) + (p_l - p_h) \qquad (5)$$

Where w_m represents the tuning parameter and m_m represents the mean brightness in the middle-intensity layer.

The global image contrast is determined by tuning parameter w_i for i $\epsilon\ \{l, m, h\}$. Although the contrast is more enhanced as the w_i increases, the resulting image is saturated and contains intensity discontinuity. Here adjust only the middle-intensity tuning parameter wm for reducing such artifacts. Since the knee transfer function tends to distort image details in the low- and high intensity layers, additional compensations performed using the gamma adjustment function. The gamma adjustment function is modified from the original version by scaling and translation to incorporate the knee transfer function as,

$$G_k(L) = \left\{\left(\frac{L}{M_k}\right)^{1/\gamma} - \left(1 - \frac{L}{M_k}\right)^{1/\gamma} + 1\right\} \qquad (6)$$

For k $\epsilon\{l, m, h\}$ Where M represents the size of each section intensity range, such as $M_l = b_l$, $M_m = b_h - b_l$ and $M_h = 1 - b_h$, L represents the intensity value, and γ represents the pre specified constant. The pre specified constant γ can be used to adjust the local image contrast. As γ increases, the resulting image is saturated around $b_l/2$, $b_h - b_l/2$ and $1 - b_h/2$ .Therefore, the γ value is selected by computing maximum values of adaptive transfer function in ranges $\{0 \le L < b_l/2\ \}$, $\{b_l \le L < (b_h - b_l/2)\}$ and $\{b_h \le L < (1 - b_h/2)\}$ which are smaller than, $b_l/2$, $b_h - b_l/2$, and $1 - b_h/2$ respectively.

The proposed adaptive transfer function is obtained by combining the knee transfer function and the modified gamma adjustment function. Three intensity transformed layers by using the adaptive intensity transfer function are fused to make the resulting contrast-enhanced image in the wavelet domain. Extract most significant two bits from the low- , middle-, and high-intensity layers for generating the weighting map, and compute the sum of the two bit values in each layer and select two weighting maps that have two largest sums. For removing the unnatural borders of fusion, weighting maps are employed with the Gaussian boundary smoothing filter. As a result, the fused image F is estimated as,

$$F = W_1 \times c_l + (1 - W_l) \times \{W_2 \times c_m + (1 - W_2) \times c_h\} \qquad (7)$$

Where W_1 represents the largest weighting map, W_2 represents the second largest weighting map, c_l represents the contrast enhanced brightness in the low-intensity layer, c_m represents the contrast-enhanced brightness in the middle-intensity layer, and c_h represents the contrast enhanced brightness in the high-intensity layer. Since Eqn. (7) represents the point operation, the pixel coordinate (x, y) is omitted. The fused LL subband undergoes the IDWT together with the unprocessed HL, LH, and HH subbands to reconstruct the finally enhanced image.

IV. ALGORITHM 2-CONTRAST ENHANCEMENT USING DOMINANT BRIGHTNESS LEVEL ANALYSIS AND PRINCIPAL COMPONENT ANALYSIS

In this section we present a new contrast enhancement algorithm for remote sensing images using dominant brightness level- and PCA [14] as shown in Fig.4.We can use DWT or DTCWT for image decomposition. This decomposes the input image into wavelet subbands and decomposes the LL subband into low, middle, and high-intensity layers by analyzing the log-average luminance of the corresponding layer. The principal component are analyzed and contrast enhancement is. All the contrast enhanced layers are fused with an appropriate smoothing, and the processed LL band undergoes Inverse transform together with unprocessed LH, HL, and HH subbands to reconstruct the finally enhanced image.

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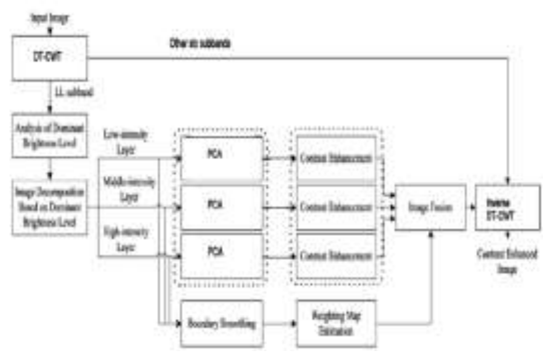

Figure 4: Contrast enhancement using DT-CWT and PCA

A. Principal Component Analysis (PCA)

Principle Component Analysis (PCA) is a statistical analytical tool that is used to explore sort and group data. PCA is a classical de-correlation technique which has been widely used for dimensionality reduction with direct applications in pattern recognition, data compression and noise reduction. What PCA does is take a large number of correlated (interrelated) variables and transform this data into a smaller number of uncorrelated variables (principal Components) while retaining maximal amount of variation, thus making it easier to operate the data and make predictions. Or as Smith (2002) puts it PCA is a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available; PCA is a powerful tool for analyzing data.

B. Steps –PCA and DTCWT

1. Apply DT-CWT to the input image.
2. Find out the brightness level in LL subband using the equation (1) based on the brightness level LL subband decomposes into low, high and middle intensity layers.
3. Finding the PCA for all corresponding layers. For this Convert each layer into one dimensional vector A = $[X_1, X_2, X_3, X_4 \ldots.]$ (i=1 to m*n) ,where m = number of rows, n=number of columns; Finding the mean value using this formula

$$K = \frac{1}{m*n} \sum_{i=1}^{m*n} a_i \quad (8)$$

4. Subtract the mean.
5. Calculate the covariance matrix.
6. Calculate the eigenvectors and Eigen values of the Covariance matrix
7. Finding Gaussian Factor with 5x5 Mask

$$h = \frac{1}{\sqrt{2\pi}} e^{(x^2+y^2)/2} \quad (9)$$

8. Finding maximum value of Gaussian coefficient (s1) And Eigen values (s).Multiply s1 with s .This value will be the enhanced Factor.
9. Multiplying all sub bands with this enhanced factor. Then perform fusion and Inverse DTCWT.
   We can perform it with DWT also.

V. ALGORITHM 3-CONTRAST ENHANCEMENT USING ALTERNATE KNEE CORRECTION METHOD

In this method the conventional knee point estimation is replaced by an alternate method which gives better results.

A. Knee correction By Mathematical Method

In algorithm, the knee points are estimated by using statistical methods. Statistical method means using the statistical property such as mean, variance etc of the image. Knee point is the point at which sudden change occurs. So an equivalent mathematical method for knee point estimation is proposed and is known as derivative method. In algebra y = f(x) be a function slope is given by the dy/dx that is derivative of the function. In this method calculate derivative of every point on the low, middle and high intensity layers and find out the point at which slope change occurs. These are the knee points of low, high and middle intensity layers. Derivative of each points are estimated by using gradient method. This knee point together with gamma function is used for the contrast enhancement of the LL layer and after appropriate smoothening and fusion process the final image is got by the inverse of the corresponding inverse transform. The block diagram of this method is given in Fig.5.

B. Steps-Alternate knee correction Method

1. Apply DT-CWT or DWT to the input image.
2. Find out the brightness level in LL subband using the equation (1) based on the brightness level LL subband decomposes into low, high and middle intensity layers.
3. Apply alternate knee correction method to find knee point
4. Calculate the gamma correction function.
5. Combining the knee and gamma to obtain contrast enhancement

6. Perform Smoothing filtering of layers.
   Finally perform fusion and Inverse DTCWT

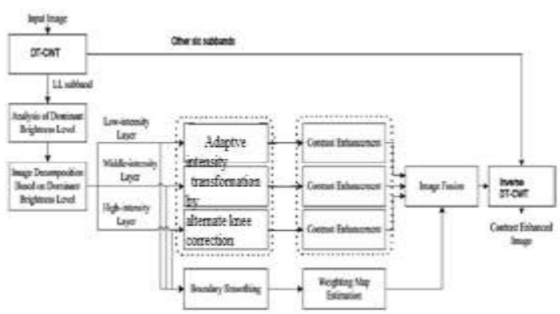

Fig. 5: Contrast enhancement using Alternate knee correction

VI. EXPERIMENTAL RESULTS

For evaluating the performance of the proposed algorithm, we tested low-contrast remote sensing images as shown in Fig. 6. The performance [15] of the proposed algorithms is compared with existing well-known algorithms including standard HE, BHE, RMSHE and DWT-SVD Methods.

The proposed method is evaluated using the Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSR), Measure of Enhancement (EME), Mean Absolute Error (MAE). PSNR is the quality measurement between the original image and the reconstructed image which is calculated through the Mean Squared Error (MSE). The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The EME [16] represents the overall image quality enhanced with preserving the average brightness level and edge details in all intensity ranges and MAE represents mean of the difference existing between two images. These parameters are calculated as follows:

$$\text{EME}=\frac{1}{k1k2}\sum_{i=1}^{k2}\sum_{k=1}^{k1}\frac{I_{max}\,(k,l)}{I_{min}\,(k,l)}\ln\frac{I_{max}\,(k,l)}{I_{min}\,(k,l)+c} \qquad (10)$$

Where k1, k2 represents the total number of blocks in an image, $I_{max}\,(k,l)$ represents the maximum value of the block, $I_{min}\,(k,l$ represents the minimum value of the block, and c represents a small constant to avoid dividing by zero.

$$\text{MSE}=\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[I(i,j)-K(i,j)]^2 \qquad (11)$$

$$\text{MAE} = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}|I(i,j)-K(i,j)| \qquad (12)$$

$$\text{PSNR} = 10 \log \frac{255^2}{MSE} \qquad (13)$$

Where I(i, j) is the input image and K(i, j) is the output image. The development of the system includes the generation the codes for each of the above steps and finally we can measure the performance of the proposed method and we can do a comparison with the older methods for better distinguishing. The performance measure includes MSE, MAE, PSNR and EME. For contrast enhancement purposes the better method for evaluating the performance is EME that is the measure of enhancement.

For the experiment, we used γ = 1.4, b_l = 0.4, and b_h = 0.7. For three different intensity layers, w_l = 1, w_m = 3, and w_h = 1 were used. The results of the standard HE method show under- or oversaturation artifacts because it cannot maintain the average brightness level. Although RMSHE and GC-CHE methods can preserve the average brightness level, and better enhance overall image quality, they lost edge details in low- and high-intensity ranges On the other hand, Demirels method could not sufficiently enhance the low-intensity range because of the singular-value constraint of the target image. Fig.6 (a) - (e) [17] shows the results of the proposed contrast enhancement method. The overall image quality is significantly enhanced with preserving the average brightness level and edge details in all intensity ranges. Here the knee point estimation is did using statistical methods. An alternate method for knee correction that is derivative method is also tested with the same image. Resultant contrast enhanced image using alternate knee correction as shown in Fig. 9. Using this knee correction contrast is not significantly improved but some brightness preservation satisfied and also improved the visual interpretation as shown in Fig.9. Fig.7 shows the enhancement using adaptive method with DTCWT. Fig.8 shows the results of enhancement using DTCWT and PCA. Here 4 LEVEL DTCWT is used. The DTCWT-PCA can achieve the sharpest enhancement result compared to other enhancement methods. EME values for different enhancement methods are listed in Table I.We also include the value of PSNR, MAE and MSE. Comparison of EME values show that the proposed Method outperforms existing enhancement methods.

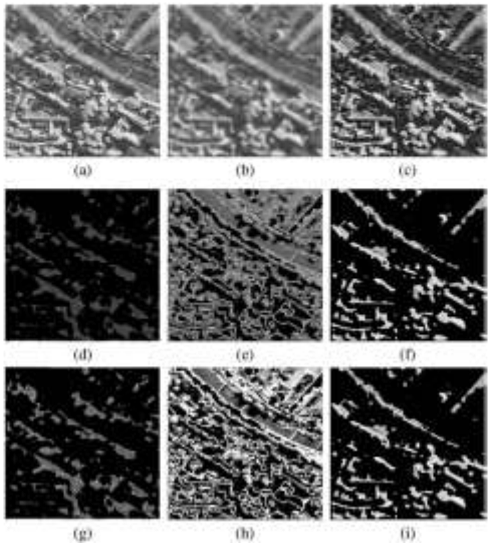

Fig. 6: Image decomposition based on the dominant brightness levels and contrast enhancement results. (a) Original image. (b) Dominant intensity analysis.(c) Enhanced result image. (d-f) Low-, middle-, and high-intensity layers. (g-i) Enhanced low-, middle-, and high intensity layers.

Fig.7: Enhanced image DTCWT and adaptive intensity transformation

Fig. 8: Enhanced image using DTCWT and PCA

Fig. 9: Enhanced image using alternate knee correction

TABLE I: COMPARISON OF RESULTS BETWEEN PROPOSED METHODS AND EXISTING METHODS

Method	EME	MSE	PSNR	MAE
DTCWT-PCA	1.3265	22.43	20.14	26.13
Alternate knee correction	0.6347	27.43	24.12	28.14
Adaptive intensity method	0.7313	24.65	20.32	24.23
SVD-DWT	0.626	42.05	15.66	35.70
RMSHE	0.680	64.31	10.12	54.06
BHE	0.690	63.17	12.15	52.34
HE	0.689	42.17	15.54	37.92

VII. CONCLUSION

In this paper we have presented different contrast enhancement method for remote sensing images. The existing algorithm decomposes the input image into four wavelet sub bands and decomposes the LL sub band into low-, middle-, and high-intensity layers by analyzing the log-average luminance. The adaptive intensity transfer functions are computed by combining the knee transfer function and the gamma adjustment function. All the contrast enhanced layers are fused with an appropriate smoothing, and the processed LL band undergoes the IDWT together with unprocessed, HL, LH and HH sub bands. This method utilizes DWT for image decomposition. But DWT produces some artifacts. To avoid the draw backs of DWT a new transform called dual tree complex wavelet transform (DTCWT) is used. The transfer function is applied for the every pixel of the image and it does not deals with which are more important one and lesser important one. To separate correlated and uncorrelated parts of an image a statistical method is used called principal component analysis (PCA). A new enhancement method is proposed based on DTCWT and PCA. Using this, dimensionality reduction is also achieved and it can effectively enhance the overall quality and visibility of local details better than existing state-of-the-art methods including HE, BHE and RMSHE. Experimental results demonstrate that the proposed algorithms can enhance the low contrast satellite images and is suitable for various imaging devices such as consumer camcorders, real-time 3-D reconstruction systems, and computational cameras.

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