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Contrast Enhancement for Remote Sensing Images with Discrete Wavelet Transform

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Abstract*— Contrast Enhancement is very important for better visual perception and color reproduction. In this paper we explained the base enhancement techniques Histogram Equalization, Bi-histogram Equalization, Contrast Enhancement using Discrete Wavelet Transform(DWT) and Singular Value Decomposition (SVD),Discrete Cosine Transform(DCT) and Singular Value Decomposition(SVD) and the proposed technique Contrast enhancement based on Dominant Brightness and Adaptive Transformation. 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*—: Bi Histogram Equalization (BHE), Discrete Cosine Transform (DCT),Discrete Wavelet Transform (DWT), Histogram Equalization (HE), Singular Value Decomposition (SV)D.

I. INTRODUCTION

The main purpose of image enhancement is to enhance or improve the quality of image with the minimum amount of MSE. Various enhancement techniques are used for this purpose both in spatial domain and frequency domain.

i). Spatial Domain Technique: Spatial domain refers to the image plane itself and approaches in this category are based on direct manipulation of pixels in an image. Histogram Equalization techniques are one of the spatial domain image enhancement techniques. This technique refers to the aggregate of the pixels composing an image. This process will be denoted by the expression given below.

$$A(x, y) = T(f(x, y)) \qquad (1)$$

Where $f(x, y)$ is input image, $g(x, y)$ is processed image and T is an operator on f, given

$$g(x, y) = A(x, y). \qquad (2)$$

ii). Frequency Domain Technique: frequency domain processing techniques are based on modifying the Fourier transform of an image.

Histogram equalization has been the most popular approach to enhance 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) has been proposed by using decomposition of two sub histograms. For further improvement a modified HE method which is based on the Singular Value Decomposition of the LL sub band of the Discrete Wavelet Transform (DWT).

In spite of the improved contrast of the image, this method tends to distort image details in low and high intensity regions. Another technique based on the Singular Value Decomposition (SVD) and Discrete Cosine Transform (DCT) has been proposed for enhancement of low contrast satellite images. The proposed technique overcomes the drawbacks such as drifting brightness, saturation in the image because pieces of important information are widespread throughout the image in the sense of both spatial locations and the intensity levels. For this reason, the proposed enhancement algorithm for satellite images not only improves the contrast but also minimizes pixel distortion in the low and high intensity regions.

A. *Discrete Wavelet Transform*

Nowadays, wavelets have been used quite frequently in image processing. They have been used for feature extraction, denoising, compression, face recognition, image super resolution. The decomposition of images into different frequency ranges permits the isolation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into certain sub bands. This process results in isolating small changes in an image mainly in high frequency sub band images. Hence, discrete wavelet transform (DWT) is a suitable tool to be used for designing a classification system. 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. This operation results in four decomposed sub band images referred to as low–low (LL), low–high (LH), high–low (HL), and high–high (HH). Where, the signal is denoted by the sequence CAj, where Aj is an integer. The low pass filter is denoted by Lo_D while the high pass filter is denoted by Hi_D. At each level, the high pass filter produces detail information, while the low pass filter associated with scaling function produces coarse approximations. At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. The frequency components of those sub-band images cover the frequency components of the original image as shown in Fig. (a)

LL	HL
LH	HH

Fig. (a) Result of 2-D DWT

Clear decomposition steps of Discrete Wavelet Transform (DWT) are shown below in Fig. (b).

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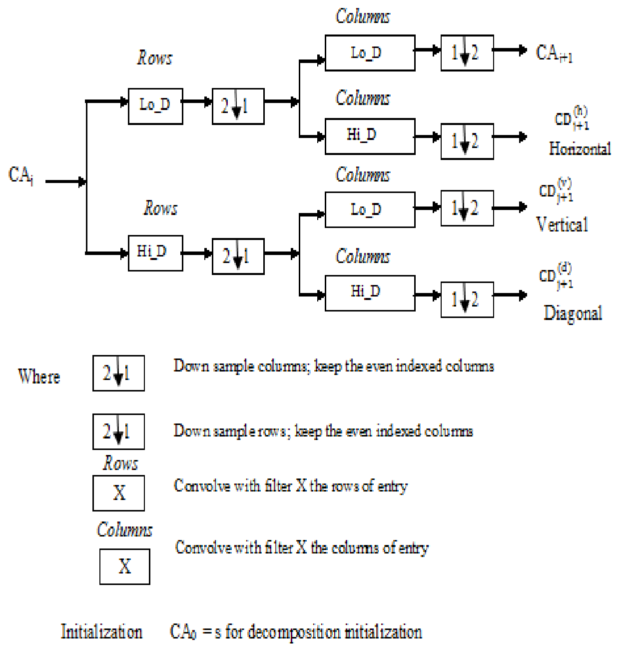

Fig. (b) 2D-DWT Functional Process.

B. Discrete Cosine Transform (DCT)

DCT was first time used in 1974 .The DCT coefficients can be quantized using visually weighted quantization values. DCT is a fast algorithm similar to FFT. The discrete cosine transform is a technique for converting a signal into elementary frequency components. It is widely used for extracting the features .The one-dimensional DCT is useful in processing of one-dimensional signals such as speech waveforms. For analysis of the two-dimensional (2-D) signals such as images, a 2-D version of the DCT is required. The DCT works by separating images into parts of differing frequencies. For an N x M matrix, the 2D-DCT is computed in a simple way. Initially, 1D-DCT is applied to each row of the matrix and then, to each column of the matrix 'x'. Thus, the transform of x is given by Eq. (3).

$$y(u,v) = \sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}\alpha_u\alpha_v\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}x(m,n)\cos\frac{(2m+1)u\pi}{2M}\cos\frac{(2n+1)v\pi}{2N} \quad (3)$$

Where $\alpha_u = \begin{Bmatrix} \frac{1}{\sqrt{2}} & u = 0 \\ 1 & u = 1,2,\dots,N-1 \end{Bmatrix}$ &

$$\alpha_v = \begin{Bmatrix} \frac{1}{\sqrt{2}} & v = 0 \\ 1 & v = 1,2,\dots,N-1 \end{Bmatrix}$$

The image is reconstructed by applying inverse DCT operation according to Eq. (4):

$$x(m,n) = \sqrt{\frac{2}{M}}\sqrt{\frac{2}{N}}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1}\alpha_u\alpha_v y(u,v)\cos\frac{(2m+1)u\pi}{2M}\cos\frac{(2n+1)v\pi}{2N} \quad (4)$$

Since, the 2D-DCT can be computed by applying 1D transforms separately to the rows and columns; it means that the 2D-DCT is separable in the two dimensions. As in the one-dimensional, each element *y (u, v)* of the transform is the inner product of the input and a basis function, but in this case, the basic functions are *M x N* matrices *x (m, n)* is the *x*, y^{th} element of the image represented by the matrix *y*, *M* is the size of the block of image on which the DCT is applied. Eq. (4) calculates on entry (*u*, *v*th) of the transformed image from the pixel values of the original image matrix.

The DCT helps to separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform; it transforms a signal or image from the spatial domain to the frequency domain. The popular block-based DCT transform segments an image non overlapping block and applies DCT to each block. It gives result in three frequency sub bands: low frequency sub band, mid frequency sub band and high frequency sub-band. DCT based enhancement is based on two facts. The first fact is that much of the signal energy lies at low-frequencies sub-band which contains the most important visual parts of the image. The second fact is that high frequency components of the image.

The basic operation of the DCT is as follows:

The input multiband satellite image is *M by N*, *f (i, j)* is the intensity of the pixel in rows i and column j, *s(x, y)* is the DCT coefficient in row and column of the DCT matrix. For most multiband satellite images, much of the signal energy lies at low frequencies; these appear in the upper left corner of the DCT.

C. Singular Value Decomposition (SVD)

The singular value based image equalization (SVE) technique is based on equalizing the singular value matrix obtained by Singular Value Decomposition (SVD). SVD of an image, which can be interpreted as a matrix, is written as follows:

$$A = U_A \Sigma_A V_A^T \quad (5)$$

Where U_A and V_A are orthogonal square matrices known as hanger and aligner, respectively, and the Σ_A matrix contains the sorted singular values on its main diagonal. The idea of using SVD for image equalization comes from this fact that Σ_A contains the intensity information of a given image.

SVD was used to deal with an illumination problem. The method uses the ratio of the largest singular value of the generated normalized matrix, with mean zero and variance of one, over a normalized image which can be calculated according to

$$\xi = \frac{\max(\Sigma_{N(\mu=0,var=1)})}{\max(\Sigma_A)} \quad (6)$$

Where $\Sigma_{N\ (\mu=0,\ var=1)}$ is the singular value matrix of the synthetic intensity matrix. This coefficient can be used to regenerate and equalized image using

$$\Xi_{equalized_A} = U_A(\xi\Sigma_A)V_A^T \quad (7)$$

Where $\Xi_{\ equalized\ A}$ is representing the equalized image *A*. This task is eliminating the illumination problem. Following are the basic ideas behind SVD: taking a high dimensional, highly variable set of data points and reducing it to a lower dimensional space that exposes the substructure of the original data more clearly and orders it from most variation to the least.

II. HISTOGRAM EQUALIZATION

Histogram equalization is a technique to obtain a uniform histogram for the output image. It flattens the histogram and stretches the dynamic range of gray levels or in other words histogram equalization maps the input image's intensity values over the range (0 to 255) so that the histogram of the resulting image will have an approximately uniform distribution. This technique is used for contrast stretching and certain modification in this technique can make it useful for preserving the brightness of the image. Due to this reason, the histogram equalization has been found to be a powerful technique for image enhancement.

Let **X** = *{X (i, j)}* denote a given image composed of L discrete gray levels denoted as $\{X_0, X_1, \ldots, X_{L-1}\}$, where $X(i, j)$ represents an intensity of the image at the spatial location (i, j) and $X(i, j) \in \{X_0, X_1, \ldots, X_{L-1}\}$. For a given image **X,** the probability density function $p(X_k)$ is defined as

$$p(X_k) = \frac{n^k}{n} \tag{8}$$

For $k = 0, 1, \ldots, L-1$, where n^k represents the number of times that the level X_k appears in the input image **X** and n is the total number of samples in the input image. Note that $p(X_k)$ is associated with the number of pixels that have a specific intensity X_k. In fact, a plot of n^k vs. X_k is known as the histogram of X**.** Based on the probability density function, we define the cumulative density function as

$$c(x) = \sum_{j=0}^{k} p(x_k) \tag{9}$$

Where $X_k = x$, for $k = 0, 1 \ldots L-1$. Note that $c(X_{L-1}) = 1$ by definition. Histogram equalization is a scheme that maps the input image into the entire dynamic range, (X_0, X_{L-1}), by using the cumulative density function as a transform function. That is, let us define a transform function $f(x)$ based on the cumulative density function as

$$f(x) = X_0 + (X_{L-1} - X_0)c(x) \tag{10}$$

Then the output image of the histogram equalization can be expressed as

$$\begin{aligned} \mathbf{Y} &= \{Y(i, j)\}, \\ Y &= f(X) \\ &\{f(X(i,j)) \mid \forall X(i,j) \in \mathbf{X}\} \end{aligned} \tag{11}$$

III. BI HISTOGRAM EQUALIZATION

Denote X_m, the mean of the image **X** and assume that $X_m \in \{X_0, X_1 \ldots X_{L-1}]$.Based on the mean, the input image is decomposed into two sub images $\mathbf{X_L}$ and $\mathbf{X_u}$ as

$$X = X_L \cup X_U \tag{12}$$

Where

$$\mathbf{X_L} = \{X(i,j) \mid X(i,j) \le X_m, \forall X(i,j) \in \mathbf{X} \tag{13}$$

And

$$\mathbf{X_U} = \{X(i,j) \mid X(i,j) \ge X_m, \forall X(i,j) \in \mathbf{X} \tag{14}$$

Note that the sub image $\mathbf{X_L}$ is composed of $\{X_0, X_1, \ldots, X_m\}$ and the other sub image **Xu** is composed of $\{X_{m+1}, X_{m+2}, \ldots, X_{L-1}\}$. Next, define the respective probability density

Functions of the sub images $\mathbf{X_L}$ and **Xu** as

$$P_L(X_k) = \frac{n_L^k}{n_L}, where\ k = 0, 1, \ldots, m \tag{15}$$

And

$$P_U(X_k) = \frac{n_U^k}{n_U}, where\ k = m+1, m+2, \ldots, L-1. \tag{16}$$

In which n_L^k and n_U^k represent the respective numbers of X_k in $\{\mathbf{X}\}_L$ and $\{\mathbf{X}\}_U$, and n_L and n_U are the total numbers of samples in $\{\mathbf{X}\}_L$ and $\{\mathbf{X}\}_U$, respectively. Note that $n_L = \sum_{k=0}^{m} n_L^k$, $n_U = \sum_{k=m+1}^{L-1} n_U^k$ and $n = n_L + n_U$. The respective cumulative density functions for $\{\mathbf{X}\}_L$ and $\{\mathbf{X}\}_U$ are then defined as

$$c_L(x) = \sum_{j=0}^{k} p_L(x_j) \tag{17}$$

And

$$c_U(x) = \sum_{j=m+1}^{k} p_U(x_j) \tag{18}$$

Where $X_k = x$. Note that $c_L(X_m) = 1$ and $c_U(X_{L-1}) = 1$ by definition. Similar to the case of histogram equalization where a cumulative density function is used as a transform function. Let us define the following transform functions exploiting the cumulative density functions

$$f_L(x) = X_0 + (X_m - X_0)c_L(x) \tag{19}$$

And

$$f_U(x) = X_{m+1} + (X_{L-1} - X_{m+1})c_U(x) \tag{20}$$

Based on these transform functions, the decomposed sub images are equalized independently and the composition of the resulting equalized sub images constitutes the output of the BHE. That is, the output image of the BHE, **Y,** is finally expressed as

$$\begin{aligned} Y &= \{Y(i,j\} \\ &= f_L(X_L) \cup f_U(X_U) \end{aligned} \tag{21}$$

Where

$$f_L(X_L) = \{f_L(X(i,j)) \mid \forall X(i,j) \in \mathbf{X_L}\} \tag{22}$$

And

$$f_U(X_U) = \{f_U(X(i,j)) \mid \forall X(i,j) \in \mathbf{X_U}\} \tag{23}$$

If we note that $0 \le c_L(x), c_U(x) \le 1$, it is easy to see that $f_L(\mathbf{X_L})$ equalizes the sub image $\mathbf{X_L}$ over the range (X_0, X_m) whereas $f_U(\mathbf{X_U})$ equalizes the sub image **Xu** over the range(X_{m+1}, X_{L-1}). As a consequence, the input image **X** is equalized over the entire dynamic range (X_0, X_{L-1}) with the constraint that the samples less than the input mean are mapped to (X_0, X_m) and the samples greater than the mean are mapped to (X_{m+1}, X_{L-1}).

IV. DWT-SVD METHOD

The singular value matrix obtained by SVD contains the illumination information. Therefore, changing the singular values will directly affect the illumination of the image. Hence, the other information in the image will not be changed. The second important aspect of this work is the application of DWT. As the illumination information is embedded in the LL sub band. The edges are concentrated in the other sub bands (i.e., LH, HL, and HH). Hence, separating the high-frequency sub bands and applying the illumination enhancement in the LL sub band only will protect the edge information from possible degradation. After reconstructing the final image by using IDWT, the resultant image will not only be enhanced with respect to illumination but also will be sharper. The general procedure of DWT-SVD technique is as own in Figure (c).

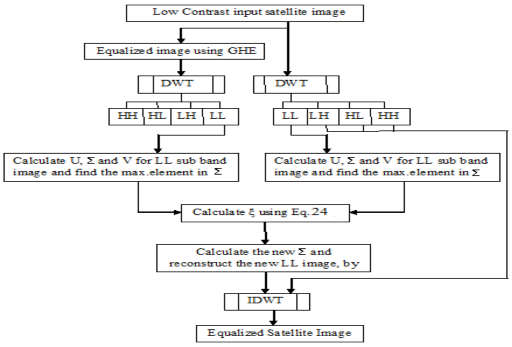

Fig. (c) Detailed steps of the DWT-SVD technique.

The input image ***A*** is first processed by using GHE to generate **Â** and then both of these images are transformed by DWT into four sub band images. The correction coefficient for the singular value matrix is calculated by using the following equation

$$\zeta = \frac{max\ (\Sigma_{LL_{\hat{A}}})}{max\ (\Sigma_{LL_A})} \qquad (24)$$

Where Σ_{LL_A} is the LL singular value matrix of the input image and $\Sigma_{LL_{\hat{A}}}$ is the LL singular value matrix of the output of the GHE. The new LL image is composed by

$$\bar{\Sigma}_{LL_A} = \zeta\ \Sigma_{LL_A} \qquad (25)$$

$$\overline{LL_A} = U_{LL_A} \bar{\Sigma}_{LL_A} V_{LL_A} \qquad (26)$$

Now $\overline{LL}_A$, LH_A, HL_A, and HH_A sub band images of the original image are recombined by applying IDWT to generate the resultant equalized image ***Â***.

$$\bar{A} = IDWT(\overline{LL}_A, LH_A, HL_A, HH_A) \qquad (27)$$

V. DCT-SVD METHOD

In method basically two parts involve in the enhancement of the satellite image. The first one is SVD and the singular value matrix. The SVD contains the illumination information in the image. So that, converting the singular values will directly change the illumination of the image, therefore the other information present in the image will be as same as before. The second most significant aspect of this method is the application of DCT as it is discussed in previous section. The DCT can be regarded as a discrete-time version of the Fourier-Cosine series. It is a close relative of DFT, a technique for converting a signal into elementary frequency components. Thus DCT can be computed with a Fast Fourier Transform (FFT). Unlike DFT, DCT is real-valued and provides a better approximation of a signal with few coefficients. This approach reduces the size of the normal equations by discarding higher frequency DCT coefficients, while avoiding the overhead of image re sampling in the DCT domain. In the DCT domain, each significance equation is dependent on the corresponding DCT frequency, and the frequency characteristics of the important structural information in the image. For the aerial images in our study, the important structural information is present in the low frequency DCT coefficients.

Hence, separating the high-frequency DCT coefficient and applying the illumination enhancement in the low–frequency DCT coefficient, it will collect and cover the edge information from possible degradation of the multiband remote sensing satellite images. DCT output is followed by applying IDCT, and thereby reconstructing the final image by using IDCT, the consequence image will be enhanced with respect to illumination and it will be sharper with good contrast.

In DCT-SVD technique, initially the input satellite image 'A' for processed by GHE to generate Â after getting this, both of these images are transformed by DCT into the lower frequency DCT coefficient, and higher–frequency DCT coefficient. Then, the correction coefficient for the singular value matrix can be calculated by using:

$$\xi = \frac{\max\ (\Sigma_{\hat{D}})}{\max\ (\Sigma_D)} \qquad (28)$$

Where $(\Sigma_{\hat{D}})$ is the lower-frequency coefficient singular matrix of the satellite input image, and (Σ_D) is the lower-frequency coefficient singular matrix of the satellite output image of the General Histogram Equalization (GHE). The new satellite image (D) is examined by:

$$\bar{\Sigma}_{\hat{D}} = \xi \Sigma_D \qquad (29)$$

$$\bar{D} = U_D \bar{\Sigma}_{\hat{D}} V_D \qquad (30)$$

Now, *D* is the lower DCT frequency component of the original image that is reorganized by applying the inverse operation (IDCT) to produce the consequence equalized image *A* as given by Eqn. (31):

$$\bar{A} = \text{IDCT}\ (\bar{D}) \qquad (31)$$

Following steps are to be undertaken to discuss the main computational process of the proposed algorithm:

Step1: In the very first step, a low contrast input satellite image has been taken for the analysis.

Step2: Equalize the satellite image using general histogram equalization technique.

Step3: After equalization, compute the discrete cosine transform for the contrast enhancement.

Step4: In this step calculate the two variables $\hat{D}$ and D from the discrete cosine transform image.

Step5: After getting $\hat{D}$ and D, SVD is applied for the calculation of the U, Σ, V and find the max element in Σ.

Step6: Calculate Max Σ_D & $\Sigma_{\hat{D}}$ Max with the help of singular value decomposition process.

Step7: Calculate ξ using Eqn. (28) ξ = max $(\Sigma_{\hat{D}})$/ max (Σ_D).

Step8: Calculate the new $\Sigma_{\hat{D}}$ using equation (29) and (30).

$\bar{\Sigma}_{\hat{D}} = \xi \Sigma_D$ & $\bar{D} = U_D \bar{\Sigma}_{\hat{D}} V_D$

Step9: Apply IDCT after getting new $\Sigma_{\hat{D}}$

Step10: Equalized satellite image.

These detailed steps are explained in the Fig.(d)

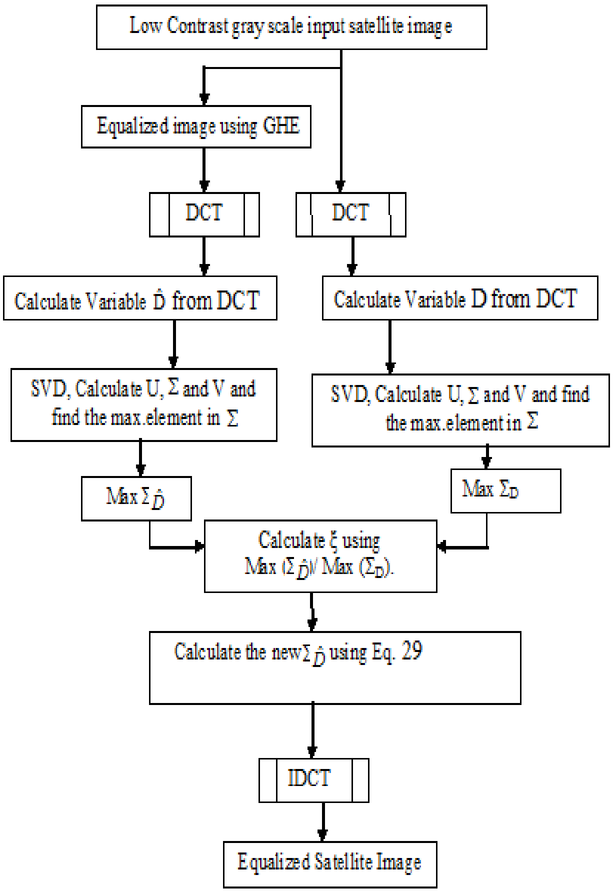

Fig. (d) Detailed steps of the DCT-SVD technique.

VI. PROPOSED TECHNIQUE

The proposed contrast enhancement algorithm first performs the DWT to decompose the input image into a set of band-limited components, called HH, HL, LH, and LL sub bands. Because the LL sub band has the illumination information, the log-average luminance is computed in the LL sub band for computing the dominant brightness level of the input image. The LL sub band is decomposed into low, middle, and high intensity layers according to the dominant brightness level. The adaptive intensity transfer function is computed in three decomposed layers using the dominant brightness level, the knee transfer function, and the gamma adjustment function. Then, the adaptive transfer function is applied for color-preserving high-quality contrast enhancement. The resulting enhanced image is obtained by the inverse DWT (IDWT).

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, we decompose the input image into multiple layers of single dominant brightness levels. To use the low-frequency luminance components, we perform the DWT on the input remote sensing image and then estimate the dominant brightness level using the log-average luminance in the LL sub band. Since high-intensity values are dominant in the bright region, and vice versa, the dominant brightness at the position (x, y) is computed as

$$D(x,y) = \exp\left(\frac{1}{N_L}\sum_{(x,y)\in S}\{\log L(x,y) + \varepsilon\}\right) \quad (32)$$

Where S represents a rectangular region encompassing (x, y), $L(x, y)$ represents the pixel intensity at (x, y), NL 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 prespecified low bound. The high intensity layer is determined in the similar manner with the prespecified 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. 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

$$P_l = b_l + w_l(b_l - m_l) \quad (33)$$

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

$$P_h = b_h + w_h(b_h - m_h) \quad (34)$$

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

$$P_{ml} = b_l - w_m(b_{ml} - m_m) + (P_l - P_h) \quad (35)$$

$$P_{mh} = b_h - w_m(b_{mh} - m_m) + (P_l - P_h) \quad (36)$$

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_l for $i \in \{l, m, h\}$. Although the contrast is more enhanced as the w_i increases, the resulting image is saturated and contains intensity discontinuity. In paper, we can adjust only the middle-intensity tuning parameter w_m for reducing such artifacts.

Since the knee transfer function tends to distort image details in the low and high intensity layers, additional compensation is 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

$$G_k(L) = \{(\frac{L}{M_k})^{\frac{1}{\gamma}} - (1 - \frac{L}{M_k})^{\frac{1}{\gamma}} + 1\} \quad (37)$$

for $k \in \{l, m, h\}$

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 prespecified constant. The prespecified 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. The three intensity transformed layers by using the adaptive intensity transfer function are fused to make the resulting contrast-enhanced image in the wavelet domain. We extract most significant two bits from the low, middle, and high intensity layers for generating the weighting map, and we compute the sum of the two bit values in each layer. We 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

$$F = W_1 \times c_l + (1 - W_1) \times \{W_2 \times c_m + (1 - W_2) \times c_h\} \quad (38)$$

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 the above equation represents the point operation, the pixel coordinate (x, y) is omitted. The fused LL sub band undergoes the IDWT together with the unprocessed HL, LH, and HH sub bands to reconstruct the finally enhanced image. The proposed algorithm is shown in Fig. (e)

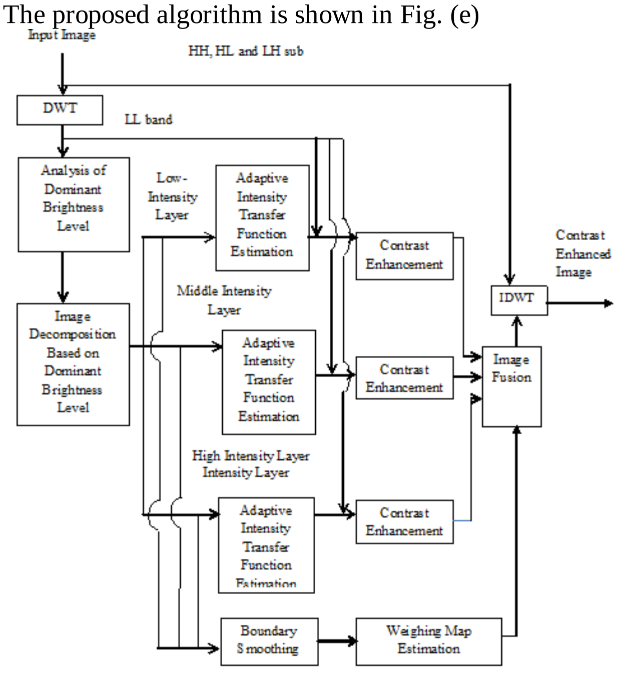

Fig. (e)Block diagram of the proposed contrast enhancement algorithm.

VII. EXPERIMENTAL RESULTS

For evaluating the performance of the proposed algorithm, we tested low-contrast remote sensing images as shown in Fig. (f). The performance of the proposed algorithm is compared with existing well-known algorithms including standard HE, BHE, DWT-SVD, and DCT-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 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:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (39)$$

Where I (i, j)-Input Image, K (i, j)-Output Image

$$PSNR = 10.\log_{10}\frac{256^2}{MSE} \quad (40)$$

$$EME = \frac{1}{k_1 k_2}\sum_{l=1}^{k_2}\sum_{k=1}^{k_1}\frac{I_{max}(k,l)}{I_{min}(k,l)+C}\ln\frac{I_{max}(k,l)}{I_{min}(k,l)+C} \quad (41)$$

Where k_1k_2 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. In this letter, we used 8 × 8 blocks and c = 0.0001.

$$MAE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|(I(m,n) - K(m,n))\right| \quad (42)$$

Where I (i, j)-Input Image, K (i, j)-Output Image

(I) Original Image

(II).Contrast Enhancement with Histogram Equalization

(III).Contrast Enhancement with Bi Histogram Equalization

(IV).Contrast Enhancement with DWT-SVD Technique

(V).Contrast Enhancement with DCT-SVD Technique

(VI).Contrast Enhancement by Proposed Method

Fig. (f) Resultant Enhanced Images by Existing and Proposed Techniques.

	EME	MSE	PSNR	MAE
PROPOSED METHOD	35.3946	24.6532	20.3273	24.2351
SVD	26.2147	38.7074	16.4089	33.3416
HE	54.8264	42.7386	15.5484	37.9217
BHE	22.7686	63.1724	12.1543	52.3428
DCTSVD	139.5981	42.1559	15.6676	36.7012

Fig. (g) Comparison of results between Proposed Method and already Existing Techniques

VIII. CONCLUSIONS

In this paper, a technique based on Dominant Brightness and Adaptive Intensity Transformation for enhancement of low-contrast satellite images has been proposed. The basic enhancement occurs due to dividing image into layers and transforming layers according to brightness preserved in them according to gamma correction. Performance of this technique has been compared with existing contrast enhancement techniques like Histogram Equalization, Bi Histogram Equalization, DWT-SVD and DCT-SVD based techniques. The experimental results show that the proposed technique gives better performance in terms of contrast (EME), brightness (MSR), PSNR and MAE of the enhanced image as compared to the other existing techniques and also it avoids over enhancement compared with DCT-SVD Technique. Thus, this technique can be considered suitable for enhancement of low contrast satellite image without changing original image quality completely.

REFERENCES

1. R. Gonzalez and R. Woods, Digital Image Processing, 3rd ed. Englewood Cliffs, NJ: Prentice-Hall, 2007.
2. Y. Kim, “Contrast enhancement using brightness preserving bi-histogram equalization,” IEEE Trans. Consum. Electron., vol. 43, no. 1, pp. 1–8, Feb. 1997.
3. H. Demirel, C. Ozcinar, and G. Anbarjafari, “Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition,” IEEE Geosci. Reomte Sens. Lett., vol. 7, no. 2, pp. 3333–337, Apr. 2010.
4. H. Demirel, G. Anbarjafari, and M. Jahromi, “Image equalization based on singular value decomposition,” in Proc. 23rd IEEE Int. Symp. Comput. Inf. Sci., Istanbul, Turkey, Oct. 2008, pp. 1–5.
5. Eunsung Lee, Sangjin Kim, Wonseok Kang, Doochun Seo, and Joonki Paik, “Contrast Enhancement Using Dominant Brightness Level Analysis and Adaptive Intensity Transformation for Remote Sensing Images”, in IEEE geoscience and remote sensing letters, vol. 10, no. 1, January 201.3
6. Multi Resolution And Contrast Enhancement Using Wavelet Transforms and Singular Value Decomposition International Journal of Advanced Trends in Computer Science and Engineering, Vol.2 , No.2, Pages : 209- 215 (2013).
7. K. Bhandari, A. Kumar and P. K. Padhy, “Enhancement of Low Contrast Satellite Images using Discrete Cosine Transform and Singular Value Decomposition”, in World Academy of Science, Engineering and Technology.