Satellite Image Optimization Correction with Measure of Enhancement Method

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***Abstract*: This paper presents a novel contrast enhancement approach based on dominant brightness level analysis and adaptive intensity transformation for satellite images. The proposed algorithm computes brightness-adaptive intensity transfer functions using the low-frequency luminance component in the wavelet domain and transforms intensity values according to the transfer function. More specifically, it first perform discrete wavelet transform (DWT) on the input images and then decompose the LL sub band into low-, middle-, and high-intensity layers using the log-average luminance. Intensity transfer functions are adaptively estimated by using the knee transfer function and the gamma adjustment function based on the dominant brightness level of each layer. After the intensity transformation, the resulting enhanced image is obtained by using the inverse DWT. The experimental results show that the proposed algorithm enhances the overall contrast and visibility of local details better than existing techniques. The proposed method can effectively enhance any low-contrast images acquired by a satellite camera and are also suitable for other various imaging devices such as consumer digital cameras, photorealistic 3-D-reconstruction systems, and computational cameras**

Index Terms— Histogram Equalization, Adaptive intensity transfer function, contrast enhancement, discrete wavelet transforms (DWT), dominant brightness level analysis, and remote sensing images.

I. INTRODUCTION

For several decades, remote sensing images have played an important role in many fields such as meteorology, agriculture, geology, astronomy, geosciences studies, education, etc. As the rising demand for high-quality remote sensing images, contrast enhancement techniques are required for better visual perception and color reproduction. One of the most important quality factors in satellite image comes from its contrast. If the contrast of an image is highly concentrated on a specific range, the information may be lost in those areas which are excessively and uniformly concentrated. The Contrast enhancement is frequently referred to as one of the most important issues in image processing. Contrast is the difference in visual properties that makes an object distinguishable from other objects and the background. In visual perception of the real world, contrast is determined by the difference in colour and brightness of an object with other objects.

II. HISTOGRAM EQUALIZATION FOR CONTRAST ENHANCEMENT

Histogram equalization is one of the common tools for improving contrast in digital photography, remote sensing, medical imaging, and scientific visualization. It is a process for recovering lost contrast in an image by remapping the brightness values in such a way that equalizes or more evenly distributes its brightness values. However, Histogram Equalization may significantly change the brightness of the entire image and generate undesirable artifacts. Therefore, many Histogram Equalization based algorithms have been developed to overcome this problem. Computer simulations and analysis are provided to compare the enhancement performance of several Histogram Equalization based algorithms.

HISTOGRAM EQUALIZATION TECHNIQUE

Histogram Equalization is a technique that generates a gray map which changes the histogram of an image and redistributing all pixels values to be as close as possible to a user –specified desired histogram. HE allows for areas of lower local contrast to gain a higher contrast. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram. Histogram equalization is a method in image processing of contrast adjustment using the image histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram. Let X={X(i,j)} denotes a image composed of L discrete gray levels denotes as X= $\{X_0,X_1,\ldots\ldots,X_{L-1}\}$.For a given Image X, the probability density function $p(X_k)$.

$$p(X_k)=n^k/n$$

Where

- $X_k=0,1,\ldots\ldots L-1$.
- n^k represents the number of times that the level X_k appears in the input image X
- n is the total number of samples in the input image.

- $p(X_k)$ is associated with the histogram of the input image which represents the number of pixels that have a specific intensity X_k.

Based on the probability density function, the cumulative density function is defined as

$$c(x) = \sum_{j=0}^{k} p(Xj)$$

Where

- $X_k = x_x$ for k=0,1,.......L-1
- $c_c(X_{L-1})$ =1 by definition.

A transform function f(x) based on the cumulative density function defined as: $f(x)=X_0+(X_{L-1}-X_0)c(x)$

Then the output image of the HE, Y={Y(i,j)}can be expressed as

$Y=f(x_x)=f\{(X(i,j)/\forall X(i,j)\in X\}$

Based on information theory, entropy of message source will get the maximum value when the message has uniform distribution property

III. DIFFERENT APPROACHES FOR APPLYING HISTOGRAM EQUALIZATION.

Histogram processing is the act of altering an image by modifying its histogram. Common uses of histogram processing include normalization by which one makes the histogram of an image as flat as possible. This is also known as contrast enhancement. Intensity transformation functions based on information extracted from image such as enhancement, compression, segmentation and description. The Histogram of digital image with the intensity levels in the range is a discrete function.

$$h(r_k) = n_k$$

Where

- r_k is the intensity value.
- n_k is the number of pixels in the image with intensity r_k.
- $h(r_k)$ is the histogram of the digital image with Gray Level r_k

Histograms are frequently normalized by the total number of pixels in the image. Assuming a M × N image, a normalized histogram. $p(r_k) = n_k$, K=0,1,2,3.........L-1 is related to probability of occurrence of r_k in the image. Where $p(r_k)$ gives an estimate of the probability of occurrence of gray level rk..The Sum of all components of a normalized histogram is equal to1. Histograms are Simple to calculate in software and also lend themselves to economic hardware implementations, thus making them a popular tool for real-time image processing. There are several approaches for applying a Histogram equalization technique for enhancing an image. Some usual existing methods are explaining as follows.

1V. GENERAL HISTOGRAM EQUALIZATION (GHE)

This type of approach uses the histogram information of the entire input image for its transformation function. Though this general approach is suitable for overall enhancement, it fails to adapt with the local brightness features of the input image. The gray levels with very high frequencies (number of occurrences) dominate over the other gray levels having lower frequencies in an image. In such a situation, GHE remaps the gray levels in such a way that the contrast stretching becomes limited in some dominating gray levels having larger image histogram components, and it causes significant contrast loss for other small ones. Suppose that an image f(x, y) is composed of discrete gray levels in the dynamic range of [0, L-1]. The transformation function $C(r_k)$ used by the GHE is defined as

$$sk = (Crk) = \sum_{i=0}^{k} p(ri) = \sum_{i=0}^{k} ni/n$$

Where $0 \leq s_k \leq 1$ and k = 0, 1, 2… L-1.

In the given equation, n_i represents the number of pixels having gray level r_i, n is the total number of pixels in the input image, and $P(r_i)$ represents as the Probability Density Function (PDF) of the input gray level r_i. Based on the PDF, the Cumulative Density Function (CDF) is defined as $C(r_k)$. Here s_k can easily be mapped to the dynamic range of [0, L-1] multiplying it by (L-1). GHE usually provides a significant improvement in image contrast, but along with some artifacts and undesirable side effects such as washed out appearance. In the equation, larger values of n_i cause the respective gray levels to be mapped apart from each other that ensures good enhancement. However, the mapping of the gray levels having smaller n_i values are forced to be condensed in a small range that makes less enhancement in such gray levels. Moreover, rounding errors may also occur in the transformation such gray levels when the output gray levels are quantized into integer values. In such cases, there is the possibility mapping more than one input gray levels to the same output gray level that leads to the loss of image details. These two phenomena are the main sources of the washed out appearances in the output image.

V. LOCAL HISTOGRAM EQUALIZATION (LHE)

It can get rid of such above mentioned problems. It uses a small window that slides through every pixel of the image sequentially and only the block of pixels that fall in this window are taken into account for HE and then gray level mapping for enhancement is done only for the center pixel of that window. Thus, it can make remarkable use of local information also. However, LHE requires high computational cost and sometimes causes over enhancement in some portion of the image. Another problem of this method is that it also enhances the noises in the input image.

VI. BRIGHTNESS PRESERVING HISTOGRAM EQUALIZATION (BPHE)

Histogram equalization is a simple and effective image enhancing technique, however, it tends to change the mean brightness of the image to the middle level of the permitted range, and hence is not very suitable for consumer electronic products, and where preserving the original brightness is essential to avoid annoying artifacts. Brightness preserving type Histogram Equalization proposes a novel extension of histogram equalization, actually histogram specification, to overcome such drawback as HE. To maximize the entropy is the essential idea of HE to make the histogram as flat as possible. Following that, the essence of the proposed algorithm, named Brightness Preserving Histogram Equalization with Maximum Entropy (BPHEME), tries to find, by the variation approach, the target histogram that maximizes the entropy, under the constraints that the mean brightness is fixed, and then transforms the original histogram to that target one using histogram specification. The existing general or global transformation function fails to take care of structural details in the image. As a result, loss of tiny details and/or enhancements of noise are observed. Alternatively, the local transformation function provides more attention to the structural details of a small region, overlooking the global impact. Thus, in our proposed method, the global transformation function is combined with the local intensity-pair distribution generated expansion function. This mixture function allows us to avail the advantages of the global HE technique, concurrently preserving the fine details of the image utilizing the spatial relationship information of neighboring pixels. Since the local transformation function will change the mean brightness, we have opted to normalize the intensity value to bring the mean brightness closer to the input mean brightness, thus, preserving the brightness preservation property.

V11. DYNAMIC HISTOGRAM EQUALIZATION (DHE)

This Dynamic Histogram Equalization (DHE) technique takes control over the effect of traditional HE so that it performs the enhancement of an image without making any loss of details in it. DHE divides the input histogram into number of sub-histograms until it ensures that no dominating portion is present in any of the newly created sub-histograms. Then a dynamic gray level (GL) range is allocated for each sub-histogram to which its gray levels can be mapped by HE. This is done by distributing total available dynamic range of gray levels among the sub-histograms based on their dynamic range in input image and cumulative distribution (CDF) of histogram values. This allotment of stretching range of contrast prevents small features of the input image from being dominated and washed out, and ensures a moderate contrast enhancement of each portion of the whole image. At last, for each sub-histogram a separate transformation function is calculated based on the traditional HE method and gray levels of input image are mapped to the output image accordingly. The whole technique can be divided in three parts – partitioning the histogram, allocating GL ranges for each sub histogram and applying HE on each of them.

VIII. BRIGHTNESS PRESERVING DYNAMIC HISTOGRAM EQUALIZATION (BPDHE)

BPDHE is an expansion of Dynamic HE (DHE) that normalizes the output intensity by bringing the mean intensity close to the mean intensity of the input image. Both BPDHE and DHE map the sub-histograms into a new dynamic range before performing the classical HE. This new dynamic range is a function of the span of each sub-histogram. Some researchers have opted to choose the local minima instead of the local maxima. Generally, within the histogram shape, there are too many maxima or minima points, and the histogram is partitioned into too many sub-histograms that ultimately end in an insignificant amount of improvement. The Brightness Preserving Dynamic Histogram Equalization (BPDHE) is the enhanced version of the DHE. Similarly, a smoothing filter is applied to histogram before the partitioning process is carried out. On the contrary, the BPDHE uses the local maxima as the separating point rather than the local minima. After the HE is implemented to each sub-histogram, brightness normalization is used to ensure the enhanced mean brightness as a close approximation to the original mean brightness. Although the BPDHE performs well in mean brightness preserving, the ratio for brightness normalization plays an important role. A small ratio value leads to insignificant contrast enhancement. For large ratio (i.e., ratio value more than1), the final intensity value may exceed the maximum intensity value of the output dynamic range. The exceed pixels will be quantized to the maximum intensity value of gray levels and produce intensity saturation problem (in MATLAB environment)

IX. LIMITATIONS IN HISTOGRAM EQUALIZATION

1. The Histogram Equalization method does not take the mean brightness of an image into account.
2. The HE method may result in over enhancement and saturation artifacts due to the stretching of the gray levels over the full gray level range.
3. Histogram equalization can be found on the fact that the brightness of an image can be changed after the histogram equalization.
4. Nevertheless, HE is not commonly used in consumer electronics such as TV because it may significantly change the brightness of an input image and cause undesirable artifacts.
5. It can be observed that the mean brightness of the histogram-equalized image is always the middle gray level regardless of the input mean.

X. IMAGE CONTRAST ENHANCEMENT USING MULTIWAVELETS AND SINGULAR VALUE DECOMPOSITION (SVD) – DEMIREL'S METHOD

Images such as satellite are essential in many areas of remote sensing. Image enhancement is a process involving changing the pixels intensity of the input images. The quality of the images depends on many factors. One of the most important factors is contrast which is created by the difference in luminance reflected from two adjacent surfaces. The main objective of image enhancement is to improve the interpretability (or) perception of information contained in the image for automated image processing applications. There are many image enhancement methods have been proposed. The most common techniques for global contrast enhancements like histogram equalizations which do not always produce good results. To overcome this issues, many number of local contrast enhancement methods have been proposed in which some form of image segmentation either in spatial (or) frequency domain followed by contrast enhancement operators on the segments. Wavelets have been used in many areas of image processing such as feature extraction, image denoising, compression, and face recognition and satellite image super resolution. The most commonly used implementation of the wavelet transform is critically sampled discrete wavelet transform (DWT) is shift variant and is unsuitable in many image processing applications. Multiwavelets may be considered as generalization of scalar wavelets. However, some important differences exist between these two types of multiresolution transforms. In particular, whereas scalar wavelets have a single scaling function and wavelet function $\psi(t)$. Multiwavelets may have two or more scaling and wavelet functions. Multiwavelets have several advantages in comparison with scalar wavelet. The features such as compact support, Orthogonality, symmetry, and high order approximation are the base features for this transformation. A scalar wavelet cannot possess all these properties at the same time. On the other hand, a multiwavelet system can simultaneously provide perfect representation while preserving length (Orthogonality), good performance at the boundaries (via linear-phase symmetry), and a high order of approximation (vanishing moments). Thus multiwavelets offer the possibility of superior performance and high degree of freedom for image processing applications, compared with scalar wavelets. When a multiresolution analysis is generated using multiple scaling functions and wavelet functions, it gives rise to the notion of multiwavelets. During a single level of decomposition using a scalar wavelet transform, the 2- D image data is replaced by four blocks corresponding to the sub bands representing either low pass or high pass in both dimensions. These sub bands are illustrated in figure. The multi-wavelets used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients. Since multiple iteration over the low pass data is desired, the scaling coefficients for the two channels are stored together. Likewise, the wavelet coefficients for the two channels are also stored together. The multi-wavelet decomposition sub bands are shown in Figure.1.1. For multi-wavelets the L and H have subscripts denoting the channel to which the data corresponds. For example, the sub band labeled L1H2 corresponds to data from the second channel high pass filter in the horizontal direction and the first channel low pass filter in the vertical direction. This shows how a single level of decomposition is done. In practice, there is more than one decomposition performed on the image.

LL	LH
HL	HH

Fig.1.1 Subband Decomposition of DWT

L_1L_1	L_1L_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2L_1	L_2H_2
H_1L_1	H_1L_2	H_1H_1	H_1H2
H_2L_1	H_2L_2	H_2H1	H_2H_2

Fig.1.2 sub band decomposition of multiwavelets

Successive iterations are performed on the low pass coefficients from the previous stage to further reduce the number of low pass coefficients. Since the low pass coefficients contain most of the original signal energy, this iteration process yields better energy compaction. After a certain number of iterations, the benefits gained in energy compaction becomes rather negligible compared to the extra computational effort. Singular value decomposition (SVD) as a general linear algebra technique is used in variety of applications. Modifying the singular value decomposition of the image is one important technique in contrast enhancement applications. Singular value decomposition (SVD) is applied on image A of size P×Q such that

$A= U_A\sum_A V_A^T$

Here V_A^T is a P×Q orthogonal matrix whose columns are the Eigen vectors of AA^T and U_A is a Q×Q orthogonal matrix whose columns are the Eigen vectors of AA^T and Σ is a Q×Q diagonal matrix with non-negative diagonal element in decreasing order of magnitudes whose entries are the square roots of the corresponding Eigen values of AA^T .In this case SVD is used to deal with the illumination problem. The SVD of this new image is calculated and the maximum singular max (A) is used to calculate the transformation factor ξ as the ratio of the largest singular value of the generated matrix over maximum value of the image.

XI. DEMIREL'S METHOD OVERVIEW

This method proposes a for satellite image equalization which is based on the SVD of an LL subband image obtained by multiwavelets. Multiwavelets are used to separate the input low contrast satellite images into one low frequency subband and 15 high frequency sub bands. The illumination information concentrated in the low frequency subband which undergoes SVD process. Inverse transform is performed to get contrast enhanced image. The proposed method has been compared with GHF; DWD-SVD based methods which show the superiority of our proposed methods. The general procedure of the proposed technique is as follows.

1. The input image I is first processed by using General histogram equalization (GHE) The resultant image is Ī.
2. (I & Ī) both images are transformed by M band Wavelet transform into sub bands.
3. The correction coefficient for the singular value matrix is calculated by using the following equation

$$\zeta = \frac{\max(\sum L1\ LI\ \bar{I})}{\max(\sum LILI\ I)}$$

Where $\sum$L1L1 is LL1 is the singular value matrix of the input image and Σ_{L1L1_1} is the singular value matrix of the output of the GHE.

XII. DEMIREL'S METHOD ARCHITECTURE

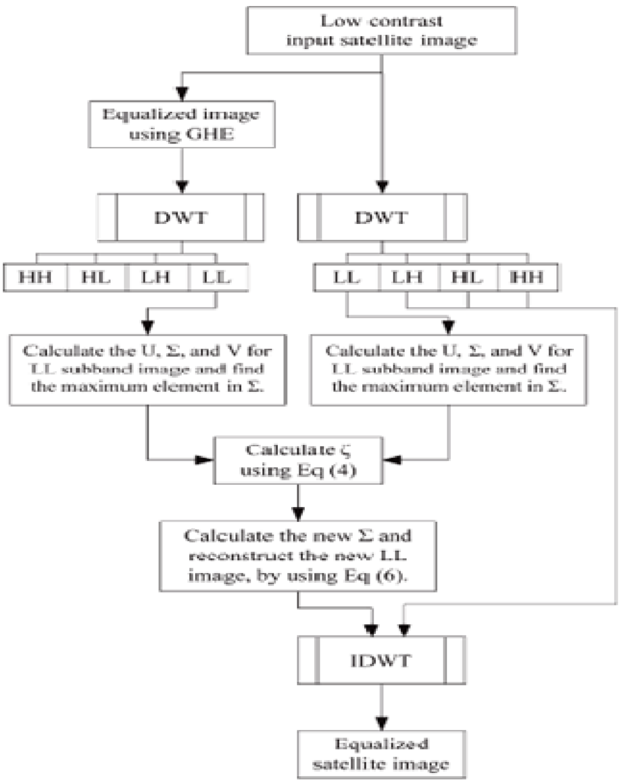


Fig 1.3: Over all Architecture

From the above fig 1.3, shows the input image we given as the low contrast satellite image. It is divided into two packets. We apply DWT directly from the satellite image another packet, after applying the histogram technique the result is given to DWT. From both packets the frequency sub bands are similarly divided into four frequency sub bands as LL, HL, LH, and HH. By taking LL sub bands similarly, we are applying the SVD technique. After that we apply the Inverse DWT to the resultant image. Then we get the final enhanced satellite resultant image.

XIII. PROPOSED METHOD USING ADAPTIVE INTENSITY TRANSFORMATION FUNCTION

The proposed method can be modified with a novel contrast enhancement approach based on dominant brightness level analysis and adaptive intensity transformation for remote sensing images. The proposed algorithm computes brightness-adaptive intensity transfer functions using the low-frequency luminance component in the wavelet domain and transforms intensity values according to the transfer function. More particularly, we first perform discrete wavelet transform (DWT) on the input images and then decompose the LL subband into low-, middle-, and high-intensity layers using the log-average luminance. Intensity transfer functions are adaptively estimated by using the knee transfer function and the gamma adjustment function based on the dominant brightness level of each layer. After the intensity transformation, the resulting enhanced image is obtained by using the inverse DWT. Although various histogram equalization approaches have been proposed in the literature, they tend to degrade the overall image quality by exhibiting saturation artifacts in both low- and high-intensity regions. The proposed algorithm overcomes this problem using the adaptive intensity transfer function. The experimental results show that the proposed algorithm enhances the overall contrast and visibility of local details better than existing techniques. The proposed method can effectively enhance any low-contrast images acquired by a satellite camera and are also suitable for other various imaging devices such as consumer digital cameras, photorealistic 3-D reconstruction systems, and computational cameras.

XIV. ANALYSIS OF DOMINANT BRIGHTNESS LEVELS

In spite of increasing demand for enhancing remote sensing images, existing histogram-based contrast enhancement methods cannot preserve edge details and exhibit saturation artifacts in low- and high-intensity regions. In this section, it presents a novel contrast enhancement algorithm for remote sensing images using dominant brightness level-based adaptive intensity transformation. 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 subband. Since high-intensity values are dominant in the bright region, and vice versa, the dominant brightness at the position (*x, y*) is computed as

$$D(x,y) = \exp\left(\frac{1}{NL}\sum_{x,y\in S}\{\log L(x,y)+\epsilon\}\right)$$

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.

XV. EDGE-PRESERVING CONTRAST ENHANCEMENT USING ADAPTIVE INTENSITY TRANSFORMATION

Based on the dominant brightness in each decomposed layer, the adaptive intensity transfer function is generated

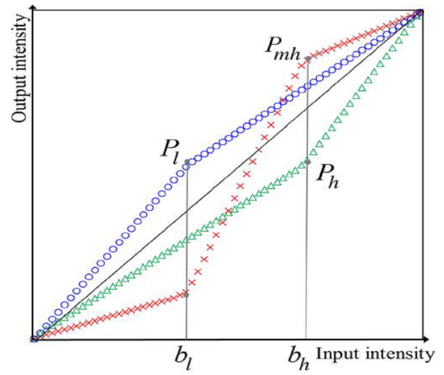


Fig. 1.4: Knee Points

Knee transfer functions for three layers using the corresponding knee points and spline interpolation. *bl* and *bh* represent low and high bounds, respectively, of intensity 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 as shown in Fig. 1.4. More specifically, in the low-intensity layer, a single knee point is computed as

$Pl = bl + wl(bl - ml)$

For the high-intensity layer, the corresponding knee point is computed as

$Ph = bh - wh(bh - mh)$

In the middle-intensity layer, two knee points are computed as

$Pml = bl - wm(bml - mm) + (Pl - Ph)$

$Pmh = bh + wm(bmh - mm) + (Pl - Ph)$

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

$G_k(L) = \{(L/M_K)^{1/\Upsilon} - (1 - L/M_K)^{1/\Upsilon} + 1\}$ for $k \in \{l,m,h\}$

Where *M* represents the size of each section intensity range, such as

$Ml = bl$, $Mm = bh - bl$, and $Mh = 1 - bh$,

L represents the intensity value, and *γ* represents the prespecified constant.

The proposed adaptive transfer function is obtained by combining the knee transfer function and the modified gamma adjustment function as shown in above Fig. Three intensity transformed layers by using the adaptive intensity transfer function are fused to make the resulting contrast-enhanced image in the wavelet domain.

OVERALL ARCHITECTURE

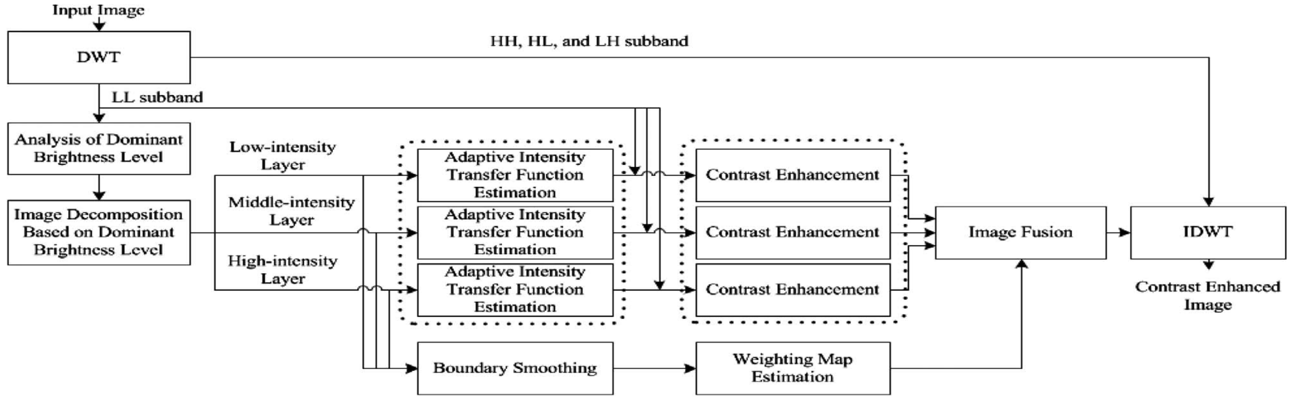


Fig. 1.5: Overall Architecture

XVI. EXPERIMENTAL RESULTS

For evaluating the performance of the proposed algorithm, we tested three low-contrast remote sensing images as shown in Figs. 4–6. The performance of the proposed algorithm is compared with existing well-known algorithms including standard HE, RMSHE, GC-CHE, and Demirel's

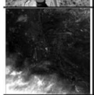
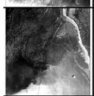
methods. For performance evaluation, we used the measure of enhancement (EME) , which is computed

$$\mathrm{EME} = \frac{1}{k1k2}\sum_{l=1}^{k2}\sum_{l=1}^{k2}\frac{\mathrm{Imax}(k,l)}{\mathrm{Imin}(k,l)+C}\ln\frac{\mathrm{Imax}(k,l)}{\mathrm{Imin}(k,l)+C}$$

Where $k1k2$ represents the total number of blocks in an image, Imax (k, l) represents the maximum value of the block, Imin (k, l) represents the minimum value of the block, and c represents a small constant to avoid

dividing by zero. Here it used 8 × 8 blocks and $c = 0.0001$. EME values for different enhancement methods are listed in Table I.

TABLE I
EME VALUES OF FIVE DIFFERENT ENHANCEMENT METHODS

	Standard HE [1]	RMSHE [4]	GC-CHE [5]	Demirel's method [6]	Proposed method
	0.025	0.010	0.125	0.764	0.786
	1.172	4.978	1.173	2.732	2.746
	1.023	0.944	0.965	1.944	2.126
	0.689	0.680	0.838	0.626	0.703

XVII . CONCLUSION

In this paper, it is presented a novel contrast enhancement method for remote sensing images using dominant brightness analysis and adaptive intensity transformation. The proposed algorithm decomposes the input image into four wavelet sub- bands 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 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 LH, HL, and HH sub bands. The proposed algorithm can effectively enhance the overall quality and visibility of local details better than existing methods including RMSHE, GC-CHE, and Demirel's methods. The experimental results demonstrate that the proposed algorithm 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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