Optimal Contrast Enhancement for Remote Sensing Images

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Abstract: This paper presents an optimal contrast enhancement approach for remote sensing images based on dominant brightness level analysis and adaptive intensity transformation for remote sensing images. The proposed system first perform discrete wavelet transform (DWT) on the input images and then split the LL sub band into low-, middle-, and high-intensity layers using the log-average luminance. The knee transfer function and the gamma adjustment function based on the dominant brightness level of each layer are used to compute the adaptive intensity transfer functions. Then a sparse representation technique is added to gain more resolution. After this transformation, the resulting optimally contrast enhanced image is obtained by using the inverse DWT. The various histogram equalization approaches proposed in the literature, degrade the overall quality of image by altering the saturation in low- and high-intensity regions, and also will not give optimal contrast enhancement. The proposed algorithm overcomes this problem by optimally enhancing the contrast and also the resolution of the input image. The proposed algorithm enhances the overall contrast and visibility of local details better than existing techniques and also gives optimal contrast. The proposed method can optimally enhance any low-contrast satellite images and are also suitable for other various imaging devices such as consumer digital cameras, photorealistic 3-D reconstruction systems, and computational cameras.

Keywords— Contrast enhancement, discrete wavelet transforms (DWT), Dominant brightness level analysis, Adaptive intensity transfer function, Remote sensing images.

I INTRODUCTION

Image processing is the study of any algorithm that takes an image as input works on it and returns an image as output. It includes image displaying and printing, image editing, image enhancement, feature detection, image compression which has various applications in the fields of biology, astronomy, Medicine, Security, Satellite imagery, personal photos etc. Various techniques exist for processing an image namely noise removal, contrast adjustment, edge detection, region detection, image compression, digital painting etc. Narrowing down, Contrast enhancement is the technique that automatically enhances and brightens images that appear dark and hazy, and applies appropriate tone correction to deliver optimal quality and clarity. The contrast of an image was formally enhanced by 3 major techniques, linear stretch, and Gaussian stretch and histogram equalization [1]-[3]. The stretch operation re distributes the values of an input image map over a wider or narrower range of values. In linear stretch the input values of the image are re distributed over the output values and then the values are linearly adjusted to obtain enhanced contrast. In similar ways, Gaussian stretch re distributes the input image values and the adjustment is made in a non linear fashion that is, the values are adjusted in minor values to gain more contrast. The histogram [1]-[3] is the graphical representation of a frequency distribution of an image showing the class intervals horizontally and the frequencies vertically. Using this histogram graph the frequency values are modified so that the overall brightness and luminance of the image is improved.

Concerning the satellite images, the images taken from the geo stationary satellites are used. The geo stationary satellites are those that are present above the equator and rotate along with the axis of the earth and with the same speed as the earth. The images from these satellites may be grey or colored, infra red or ultra violet images taken from a longer distance. Such images contain most of the information hidden due to the fuzzy and hazy nature of the image. To improve the image readability and image information collection ability the image must be enhanced in terms of various features of the image such as image brightness, image luminance, image contrast etc. Some of the disturbing features must reduced such as noise, blur etc.

II. PROPOSED SYSTEM

In proposed to improve the resolution of the source image, a separate image super-resolution step can be performed. It is based on the use of sparse representations, and consists of three steps. First, input image into a set of band-limited components, called HH, HL, LH, and LL sub bands by using DWT[6][7]. 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 [8]-[10]. The low-resolution source images are interpolated and decomposed into high- and low-frequency components. Then sparse representation can be applied on LL, LH an LH sub bands of image to get super resolution. Sparse coefficients from these components are then computed and fused by using image fusion rules. The adaptive intensity transfer function is computed in three decomposed layers using the dominant brightness level, the knee transfer function [11], and the gamma adjustment function [12][13]. 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) [6][7].

2.1 IMAGE ACQUISITION AND DECOMPOSITION OF SOURCE IMAGE USING DWT

Remote sensed image is taken as the input. This input image is decomposed into a set of band-limited components, called HH, HL, LH, and LL sub bands by using Discrete Wavelet Transform [6][7] as shown in Fig.1.0.

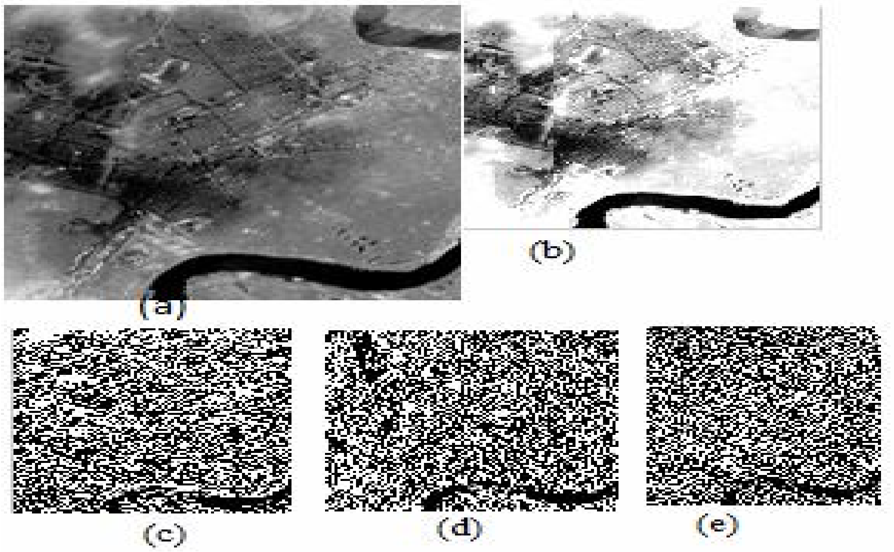

Fig.1.0 (a) Input image (b) LL (c) HH (d) HL (e) LH

2.2 ANALYSIS OF DOMINANT BRIGHTNESS LEVEL

After the input image is split into four sub bands, the LL sub band is taken for further analysis since the luminance feature is low in this sub band. The Dominant brightness level [8]-[10] of this sub band is calculated using the following formula,

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

Where S is a rectangular region encompassing (x, y), $L(x, y)$ is the pixel intensity at (x, y), N_L is 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 dominant brightness of each pixel is calculated and stored in a matrix. 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, 0.4 and 0.7 were taken for the low and high bounds, respectively.

2.3 ESTIMATION OF ADAPTIVE INTENSITY TRANSFORMATION

The next step is to estimate the adaptive intensity transformation. This is done by using the knee transfer and gamma adjustment functions.

2.3.1 KNEE TRANSFER FUNCTION

The knee transfer function [11] is used to stretch the low intensity layer by calculating the knee points based on the dominant brightness level of each pixel. The knee points on the low intensity layer is calculated using,

$$P_l = b_l + w_l(b_l - m_l)$$

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

$$P_h = b_h - w_h(b_h - m_h)$$

Where b_h is the high bound, w_h is the tuning parameter, and m_h is the mean brightness in the high intensity The middle intensity knee points are computed using,

$$P_{ml} = b_l - w_m(b_{ml} - m_m) + (P_l - P_h)$$
$$P_{mh} = b_h + w_m(b_{mh} - m_m) + (P_l - P_h)$$

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

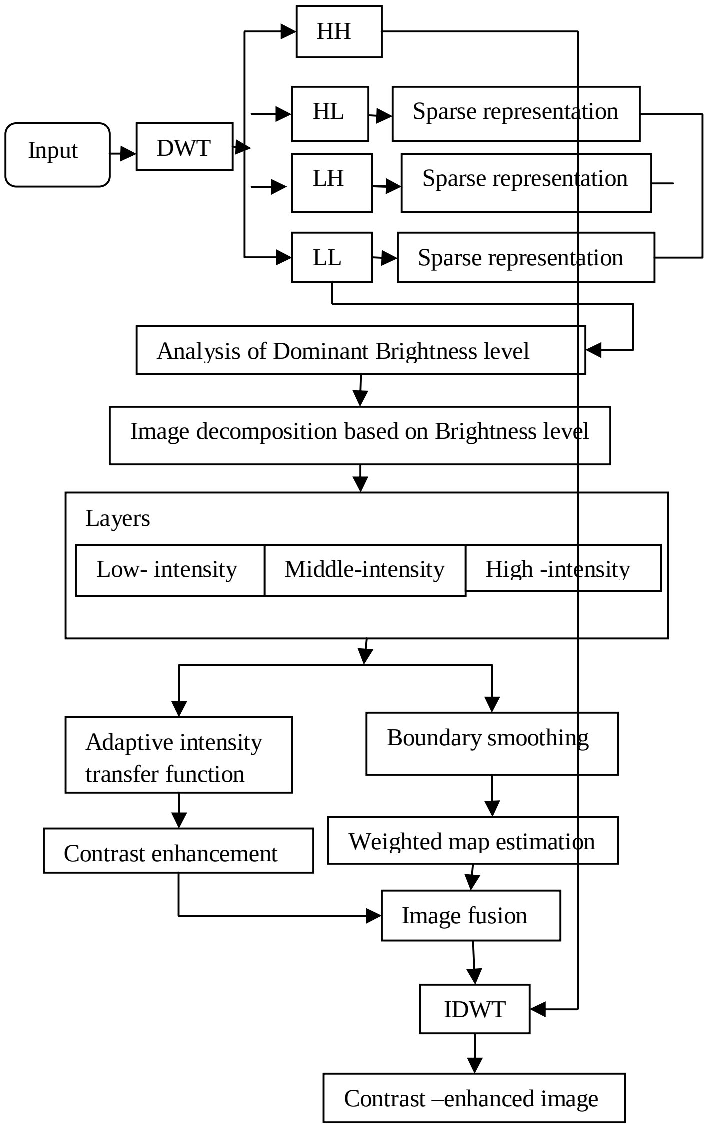

Fig.1.1 Block diagram of the proposed optimal contrast enhancement algorithm

2.3.2 GAMMA ADJUSTMENT FUNCTION

The knee transfer function tends to distort the image's low and high intensity layers. Hence it is adjusted using the gamma adjustment function [12][13]. The gamma adjustment function is modified from the original version by scaling and translation to incorporate the knee transfer function as,

$$G_k(L) = \left\{ \left(\frac{L}{M_k}\right)^{\frac{1}{\gamma}} - \left(1 - \frac{L}{M_k}\right)^{\frac{1}{\gamma}} + 1 \right\}, \quad \text{for } k \in \{l, m, h\}$$

Where M is 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 is the intensity value, and γ represents the prespecified constant. Three intensity transformed layers by using the adaptive intensity transfer function are fused to make the resulting contrast-enhanced image in the wavelet domain. The most significant two bits from the low-, middle-, and high-intensity layers are extracted for generating the weighting map, and the sum of the two bit values are computed in each layer. Then two weighting maps that have two largest sums are selected. 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 brought using,

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

Where W_1 is the largest weighting map, W_2 is the second largest weighting map, c_l is the contrast enhanced brightness in the low-intensity layer, c_m is the contrast-enhanced brightness in the middle-intensity layer, and c_h is the contrast-enhanced brightness in the high-intensity layer.

2.4 SPARSE REPRESENTATIONS

The HL, LH, LL sub bands are subjected to sparse super resolution technique. The main idea of sparse representation is that a given image input is x ∈ Rn can be represented by a linear combination of a few atoms in an over complete dictionary D ∈ Rn_m (n < m). In other words, the signal x can be expressed as x = Da, where a ∈ Rm is the coefficient vector with only a few nonzero elements. The sparsest a can be obtained by solving the following optimization problem

$$\min_{\alpha} \|\alpha\|_0 \quad \text{subject to} \quad \|x - \mathbf{D}\alpha\|_2^2 \leqslant \varepsilon,$$

Where eP0 is an error tolerance and ||_||0 denotes the ‘0-norm (which counts the number of nonzero entries).
Then greedy algorithm is used, which iteratively updates the estimated sparse coefficients by choosing one or several atoms from the dictionary. A representative greedy algorithm with low computational complexity is the orthogonal matching pursuit (OMP), which iteratively updates the estimated sparse coefficients by choosing the most relevant atom. Then the sparse sub bands and the HH sub band are fused together using the inverse discrete wavelet transform. This module is under progress.

III. CONCLUSION

The satellite images can hide parts of important information which cannot be easily identified when image’s features such as contrast, resolution are low. Hence the proposed technique produces better contrast enhancement in an optimal way and is also more efficient. The advantages of using this technique are 1) Enhanced contrast can be obtained. 2) Better enhance overall image quality. 3) Super resolution of the images can be obtained. 4) Preserves the average brightness level. 5) Lower computational complexity.

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