Contrast Enhancement for Remote Sensing Images using Discrete Wavelet Transform, Brightness Level Analysis and Lapped Transform

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***Abstract*— A new satellite image contrast enhancement technique based on the Discrete wavelet transform (DWT), Brightness level analysis and lapped transform has been proposed. By the use of discrete wavelet transform wavelet transform, the input image decomposed into four directional sub-bands and the brightness level is computed in the LL subband using log average luminance. Based on the brightness level LL decomposes into low, middle and high intensity layers. apply lapped transform of the each decomposed layer image and reconstructs the enhanced image by applying 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, photorealistic3-D reconstruction systems, and computational cameras.**

Keywords*— Contrast enhancement, Discrete wavelet transform (DWT), dominant brightness level analysis, remote sensing images, Lapped transfrom

I.INTRODUCTION

Contrast enhancement is frequently referred to as one of the most important issues in image processing. Contrast is created by the difference in luminance reflected from two adjacent surfaces. In other words contrast is the deference in visual proper-ties that makes an object distinguishable from other object and the back-ground. In visual perception contrast is determined by the difference in color and brightness of the object with other object. It is the difference between the darker and the lighter pixel of the image; if it is big the image will have high contrast our visual System is more sensitive to contrast than absolute luminance; therefore, we can perceive the world similarly regardless of the considerable changes in illumination conditions. 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 information may be lost in those areas which are excessively and uniformly concentrated. The problem is to optimize the contrast of an image in order to represent all. Contrast enhancements improve the Perceptibility of objects in the scene by enhancing the brightness difference between objects and their backgrounds. Contrast enhancement processes adjust the relative brightness and darkness of objects in the scene to improve their visibility.

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] and dualistic sub image HE [3] methods have been proposed by using decomposition of two sub histograms. For further improvement, the recursive mean-separate HE (RMSHE) [4] method iteratively performs the BHE and produces separately equalized subhistograms. However, the optimal contrast enhancement cannot be achieved since iterations converge to null processing.

Recently, the gain-controllable clipped HE (GC-CHE) has been proposed by Kim and Paik [5]. The GC-CHE method controls the gain and performs clipped HE for preserving the brightness. Demirel *et al.* have also proposed a modified HE method which is based on the singular-value decomposition of the LL subband of the discrete wavelet transform (DWT) [6], [7]. 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. To achieve this goal, we present a novel contrast enhancement method for remote sensing images using dual tree complex wavelet transform, brightness level analysis and Principal component analysis.

More specifically, the proposed contrast enhancement algorithm first performs the DWT to decompose the input image into a set of band-limited components. LL subband has the illumination information [6], the log-average luminance is computed in the LL subband for computing the dominant brightness level of the input image [8]–[10]. The LL subband is decomposed into low-, middle-, and high-intensity layers according to the dominant brightness level. The lapped transform is applied for the three intensity layers; finally enhanced image is reconstructed by using inverse IDWT

II. DISCRETE WAVELET TRANSFORM

The decomposition of images into various frequency ranges permits the isolation of the frequency components introduced by "intrinsic deformations" or "extrinsic factors" into certain subbands [17]. This process results in isolating small changes in an image mainly in low-frequency sub band images. 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 Decomposition results in four decomposed subband images referred to as low–low (LL), low high (LH), high–low (HL), and high–high (HH)

III. 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, we present a novel contrast enhancement algorithm for remote sensing images using dual tree complex wavelet transform, brightness level analysis and lapped transform shown in Fig. 1.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 per-form the DT-CWT on the input remote sensing image and then estimate the dominant brightness level using the log-average luminance in the LL subband [8]. Since high-intensity values are dominant in the bright region, and vice versa, the dominant the dominant Brightness at the position (x,y) is computed as:

$$D\left(x,y\right)=exp(\frac{1}{p}\sum_{(x,y)\in S}\{\log L\left(x,y\right)+\text{£}\ (1)\}) \tag{1}$$

Where S represents a rectangular region encompassing(x,y), L(x,y) represents the pixel intensity at(x,y) ,'P'represents the total number of pixels in S, and £ 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.

IV LAPPED TRANSFORM

The idea of a lapped transform (LT) maintaining orthogonality and nonexpansion of the samples was developed in the early 80s at MIT by a group of researchers unhappy with the blocking artifacts so common in traditional block transform coding of images. The new idea was to extend the basis function beyond the block boundaries. Hence creating an overlap, inorder to eliminate the blocking effect. This idea was to create overlapping blocks, so that it would be the same as if there was no overlap, and that the transform would maintain orthogonality[19].

For lapped transforms the basis vectors have length L, such that L>M, extending across block boundaries. Thus, the transform matrix is no longer square and most of the equations valid for block transforms do not apply to LT. We concentrate on orthogonal LTs and consider L=NM, where N is the overlap factor. N, M and hence L are integers. As in the block transforms, we define transform matrix with the orthonormal basis vectors as its rows. In lapped transform, transformation matrix P of dimensions $M\times L$ can be divided into square $M\times M$ submatrices $P_i(i=0,1,.,..,..,N-1)$ as $P=[P_0P_1.....P_{N-1}]$. The orthogonality property does not hold because P is no longer square matrix.

We divide the signal into blocks, each of size M, we would have the vectors x_m and y_m as eqns. (1) and (2). These blocks are not used by the LTs in a straightforward manner. The actual vector which is transformed by the matrix P has to have L samples. At block number m, it is composed of the samples of x_m plus $L-M$ samples. These samples are chosen by picking $(L-M)/2$ samples at each side of the block x_m, as in Fig.1 for N=2.

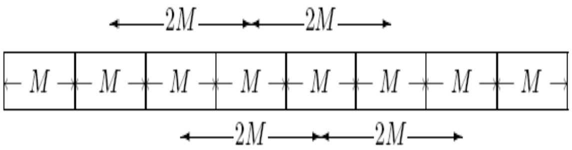

Fig.1: The signal samples are divided into blocks of M samples

The lapped transform uses neighboring block samples, as in this example for N=2, i.e. L=2M, yielding an overlap of $(L-M)/2=M/2$ samples on the either side of the block. However the number of transform coefficients at each block is M, and in this respect there is no change in the way we represent the transform-domain blocks y_m.The input vector of length L is denoted as v_m ,which is centered around the block x_m and is denoted as:

$$v_m^T = [x(mM-(N-1)\frac{M}{2}) ...... x(mM+(N+1)\frac{M}{2}-1)]$$
(2)

Then, we have $y_m = Pv_m$. The inverse transform is not direct as in the case of block transform. i.e., with the knowledge of y_m we do not know the samples in the support region of v_m, and neither in the support region of x_m. We can reconstruct a vector $\hat{v}_m = P^T y_m$ where $\hat{v}_m \neq v_m$ .To reconstructs the original sequence, accumulate the results of the vectors $\hat{v}_m$, in a sense that a particular sample $x(n)$ was included in the region of support of the corresponding v_m.

Reversible Time Domain Lapped Transform (RTDLT) [20] belongs to block transform ;thus, the source image will be segmented into adjacent nonoverlapping blocks before transforming. All lapped transforms can be viewed as post- and pre-processing of the DCT coefficients with the quantizer in between. LOT has been shown to comprise of either i) cross – boundary post-processing of a certain block transforms output or ii) cross-boundary pre-processing of a block transforms input.

IV. PROPOSED METHOD

The proposed algorithm decomposes the input image into six 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 lapped transform is computed for each layer and all the contrast-enhanced layers are fused with an appropriate smoothing, and the processed LL band undergoes the IDWT together with unprocessed subbands.

V. STEPS OF IMPLEMENTATION

Step 1: Read the input image

Step 2: Apply DT-CWT for that image

Step 3: Find out the brightness level in LL subband using the formula (1)

Step 4: Based on the brightness level LL subband decomposes into low, high and middle intensity layers

Step 5: Applying the lapped transform for three layers obtained in step (4)

Step 6: Three intensity transformed layers by using the lapped transform are fused to make the resulting contrast-enhanced Image in the wavelet domain.

Step 7: 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

$$F = W_1 * c_l + (1-W_1) * \{W_2 * c_m + (1-W_2) * c_h\} \quad (3)$$

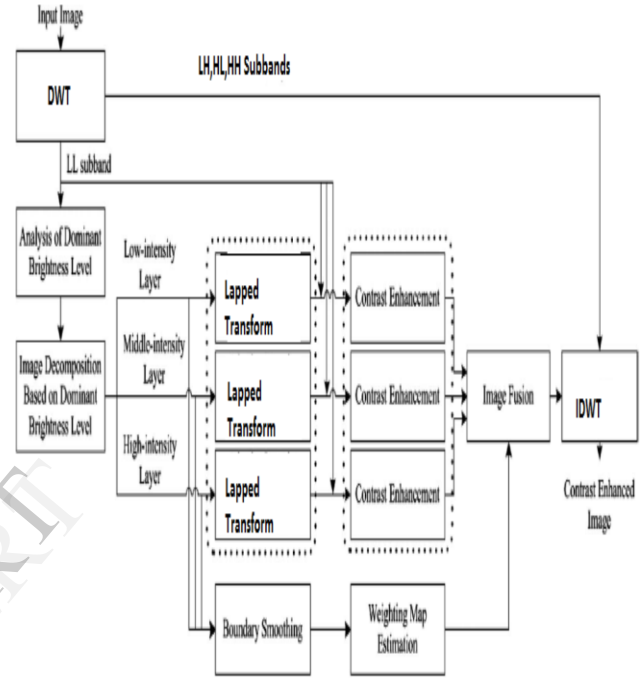

Fig.2: Block diagram of proposed method

Where $W1$ represents the largest weighting map, $W2$ represents the second largest weighting map, cl represents the contrast enhanced brightness in the low-intensity layer, cm represents the contrast-enhanced brightness in the middle-intensity layer, and ch represents the contrast-enhanced brightness in the high-intensity layer. Since (2) represents the point operation, the pixel coordinate (x, y) is omitted. The fused LL subband undergoes the IDWT together with the unprocessed other six subbands to reconstruct the finally enhanced image.

VI. EXPERIMENTAL RESULTS

In this section, simulation is carried out to evaluate the performance of the proposed method. Fig 2(a) shows Original low-contrast image from Satellite Imaging Corporation. In our experiments, proposed method is compared with standard HE, RMSHE, GC-CHE, Demirel's,, and Adaptive intensity transformation . 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 as. On the other hand, Demirel'smethod could not sufficiently enhance the low-intensity ranges because of the singular-value constraint of the target image. And the adaptive intensity transformation fails to enhance all types of images. Figs.2(b) show 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 .For performance evaluation, we used the measure of enhancement (EME) [15], which is computed as:

$$EME = \frac{1}{K_1 K_2} \sum_{i=1}^{K_2} \sum_{k=1}^{K_1} \frac{I_{max}(k,l)}{I_{min}(k,l)+c} \ln \frac{I_{max}(k,l)}{I_{min}(k,l)+c} \quad (4)$$

Where k_1,k_2 represents the total number of blocks in an image, $I_{max}(k,l)$ represents maximum value of the block,$I_{min}(k,l)$ represents minimum value of block and c represents a small constant to avoid dividing by zeros. This letter, we used 8 x 8 blocks and c = 0.0001.

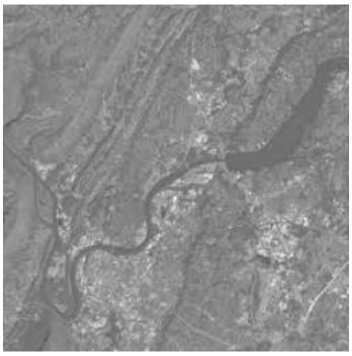

Fig: Orginal satellite image

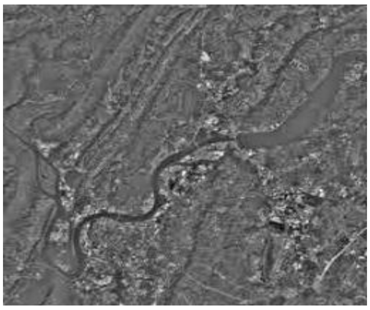

Fig. Enhanced image using proposed method

EME values for different enhancement methods are listed in Table I. Comparison of EME values show that the proposed method outperforms existing enhancement methods.

TABLE 1: EME VALUES OF FIVE DIFFERENT ENHANCEMENT METHODS

Name of methoid	HE [1]	RMSBE [4]	GC CHE [5]	Demirel's Method [6]	Adaptive Method [7]	Proposed method
EME	1.023	0.944	0.965	1.944	2.216	3.145

VII.CONCLUSION

We have presented a novel contrast enhancement method for remote sensing images using DWT , beightness level analysis and lapped transform. The proposed algorithm 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 lapped transform is applied for all these layers and all the contrast enhanced Layers are fused with an appropriate smoothing, and the processed LL band undergoes the IDT-CWT together with unprocessed other subbands. The proposed algorithm can effectively enhance the overall quality and visibility of local details better than existing state-of-the-art methods including RMSHE,GC-CHE, Demirel's and adaptive intensity methods. 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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