International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Contrast Enhancement Using Dominant Brightness Level Analysis and Adaptive Intensity Transformation for Remote Sensing Images

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Abstract: ***This letter presents 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 specifically, we 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. 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 is also suitable for other various imaging devices such as consumer digital cameras, photorealistic 3-D reconstruction systems, and computational cameras.***

Keywords: Adaptive intensity transfer function, contrast enhancement, discrete wavelet transform (DWT), dominant brightness level analysis, remote sensing images.

1. Introduction

For several decades, remote sensing images have played an important role in many fields such as meteorology, agriculture, geology, education, etc. As the rising demand for high-quality remote sensing images, contrast enhancement techniques are required for better visual perception and color reproduction.

Histogram equalization (HE) 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) and dualistic sub image HE 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 sub histograms. 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. 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 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. 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 wide spread 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 dominant brightness level analysis and adaptive intensity transformation. More specifically, 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).

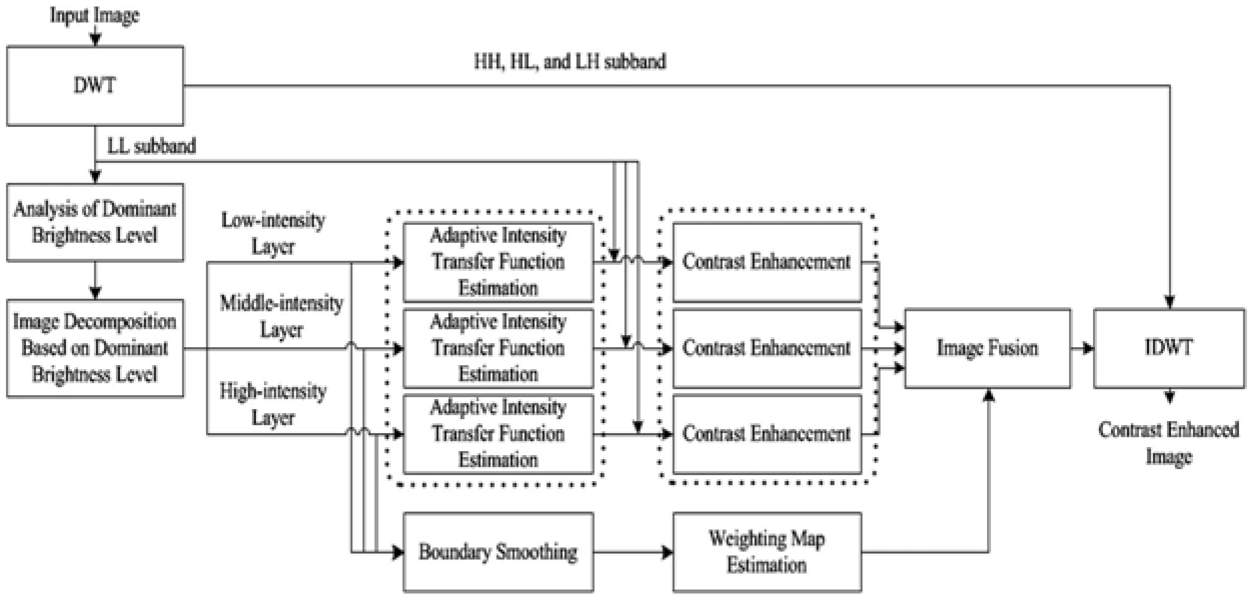


Figure 1: Block diagram of the proposed contrast enhancement algorithm.

2. 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 an ovel contrast enhancement algorithm for remote sensing images using dominant brightness level-based adaptive intensity transformation as 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 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

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

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 decomposed low-, middle-, and high-intensity layers re shown in Fig. 2. The low-intensity layer has the dominant brightness lower than the pre-specified low bound. The high intensity layer is determined in the similar manner with the pre specified high bound, and the middle-intensity layer has

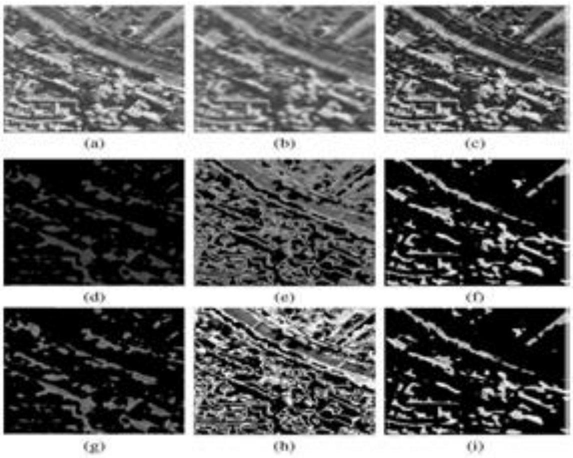


Figure 2: Image decomposition based on the dominant brightness levels and contrast enhancement results. (a) Original image. (b) Dominant intensity analysis. (c) Enhanced result image. (d–f) Low, middle, and high intensity layers. (g–i) Enhanced low, middle , and high-intensity layers.

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.

3. Edge-Preserving Contrast Enhancement Using Adaptive Intensity Transformation

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

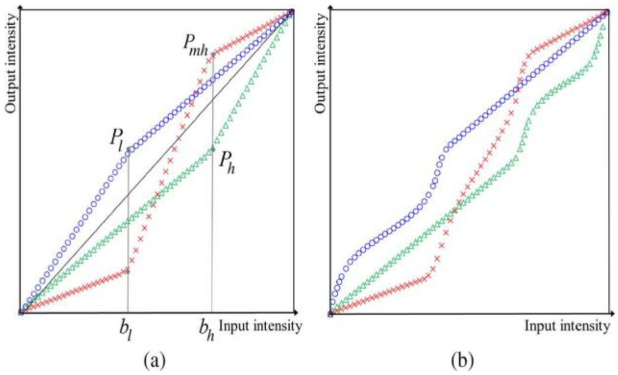


Figure 3: (a) Knee transfer functions for three layers using the corresponding knee points and sp line interpolation. *Bl* and *bh* represent low and high bounds, respectively, of intensity **O**,***x***, and **Δ** represent low, middle and high intensity layers, respectively. (b) Adaptive intensity transfer functions for three layers.

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. 3(a).

4. Experimental Results

For evaluating the performance of the proposed algorithm, we tested three low-contrast remote sensing images as shown in Figs. 4–6(a). The performance of the proposed algorithm is compared with existing well-known algorithms including standard HE, RMSHE, GC-CHE, and Demirel's methods. For the experiment, we used γ = 1.4, *bl*= 0.4, and *bh*=0.7. For three different intensity layers, *wl*= 1, *wm*= 3, and *wh*= 1 were used.

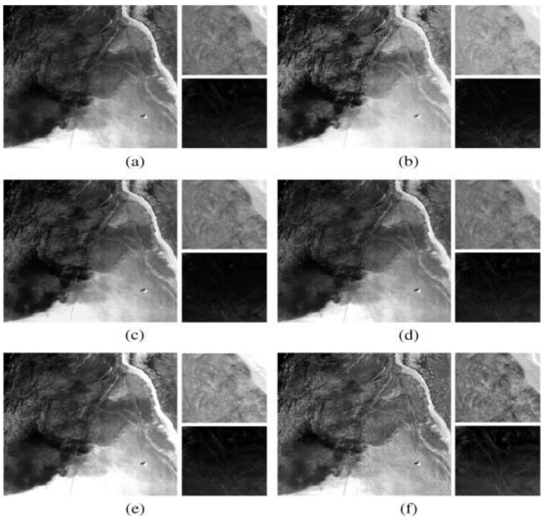
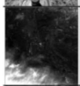
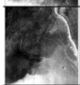


Figure 4: (a) Original satellite image from KARI; contrast-enhanced images by using (b) the standard HE, (c) RMSHE, (d) GC-CHE, (e) Demirel's, and (f) the proposed methods

Figs. 4–5 show the results of contrast enhancement using the standard HE, RMSHE, GC-CHE, Demirel's, and the proposed methods. As shown in Figs. 4–5(b), the results of the standard HE method show under- or oversaturation artifacts because It can not 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 shown in Figs. 4–5(c) and (d). On the other hand, Demirel's method could not sufficiently enhance the low-intensity range as shown in Figs. 4–5(e) because of the singular-value constraint of the target image. Figs. 4–5(f) 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) which is computed.

Table 1: Eme Values Of Five Different Enhancementmethods

	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

5. Conclusion

In this letter, we have 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 sub band 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 state-of-the-art methods including RMSHE,GC-CHE, and Demirel's 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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