

Edge Preserving Contrast Enhancement Method Using PCA in Satellite Images

Sruthy M Sreedhar, Sarayu Vijayan

Abstract— This paper presents a contrast enhancement approach based on DWT using dominant brightness level analysis and adaptive intensity transformation for remote sensing images. The proposed algorithm computes brightness analysis using the low frequency components in the wavelet domain then these components are transferred using intensity transformation function. Here we first perform DWT (Discrete Wavelet Transform), then the input image is divided into four subbands. The LL subband is decomposed into Low-, middle- and high intensity layers using a log-average luminance function performed in the brightness level analysis step. The optimal transfer function is estimated for three layers using knee transfer function and gamma adjustment function. Then weighting map estimation is performed for three intensity layers and we use boundary smoothing to remove unnatural borders of fusion. After these an enhanced image is obtained using inverse DWT. This enhanced image undergoes PCA (Principle Component Analysis) to get the finally enhanced image. The proposed algorithm overcomes the saturation artifacts in the low and high intensity regions using the adaptive intensity

Index Terms— Contrast Enhancement, DWT (Discrete Wavelet Transform); Dominant Brightness Level Analysis; Adaptive Intensity Transformation; PCA (Principle Component Analysis)

I. INTRODUCTION

Satellite images are used in many applications such as geosciences studies, astronomy, and geographical information systems. Satellites take images from space, but most of the information are not clear with low contrast. One of the most important quality factors in satellite image comes from its contrast. 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. There have been several techniques to overcome the contrast issues such as general histogram equalization techniques. Histogram equalization (HE) [1] is the most popular approach to enhancing the contrast, but this method cannot preserve 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 subimage HE [3] methods have been proposed by using decomposition of two

subhistograms. These techniques further improved as the recursive mean-separate HE (RMSHE) [4] method. But in these methods the optimal contrast enhancement cannot be achieved since iterations converge to null processing. In the gain-controllable clipped HE (GC-CHE) and singular-value decomposition of the LL subband of the discrete wavelet transform (DWT) [5], [7] tends to distort image details in low- and high-intensity regions.

In the above existing various contrast enhancement approaches in remote sensing images, the common drawbacks are drifting brightness, saturation, and distorted details, these need to be minimized because pieces of important information are widespread throughout the image in the sense of both spatial locations and intensity levels. They tend to degrade the overall image quality by exhibiting saturation artifacts in both low- and high-intensity regions. The performance of the image will be less.

To overcome the above problems here we propose a novel contrast enhancement method based on discrete wavelet transform (DWT) using brightness level analysis and adaptive intensity transformation. 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 subbands. Because the LL subband has the illumination information, 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 adaptive intensity transfer function [6] is computed in three decomposed layers using the knee transfer function, and the gamma adjustment function. Then, the adaptive transfer function is applied for colour-preserving high-quality contrast enhancement. The weighting map is estimated in three layers and Gaussian boundary smoothing is performed for these three layers. The contrast enhanced layers and weighting map estimated layer combined with boundary smoothed layers and LL subband layer undergoes inverse DWT (IDWT) together with LL, LH, HH layers. This enhanced resultant image undergoes principle component analysis (PCA) to get the finally enhanced image.

II. PROPOSED METHOD

A new edge preserving contrast enhancement technique in satellite images using PCA has been proposed here. This 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 using adaptive intensity transformation method. The weighting map estimation and boundary smoothing is performed for three intensity layers. The smoothed layer and weighting map estimated layer are combined into one layer. The contrast enhanced intensity layers and LL subband combined to form another one layer.

Sruthy M Sreedhar, B.Tech in Information Technology from University College of Engineering Thodupuzha under M.G. University Kerala, M.Tech in Image Processing from College of Engineering Chengannur under Cochin University of Science and Technology.

Sarayu Vijayan, Assistant Professor, Department of Computer Engineering, College of Engineering Chengannur under Cochin University of Science and Technology.

These two layers are obtained in the wavelet domain, so these combined layers separately undergoes inverse DWT together with LL, LH, HH layers. Then we get an output image from inverse DWT. This image undergoes principle component analysis(PCA) to get the resultant image. Fig.1 represents the overview of the proposed method.

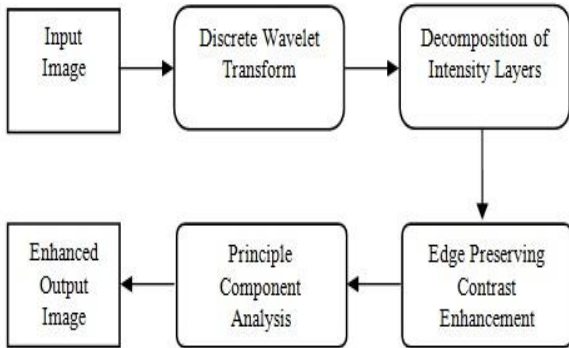
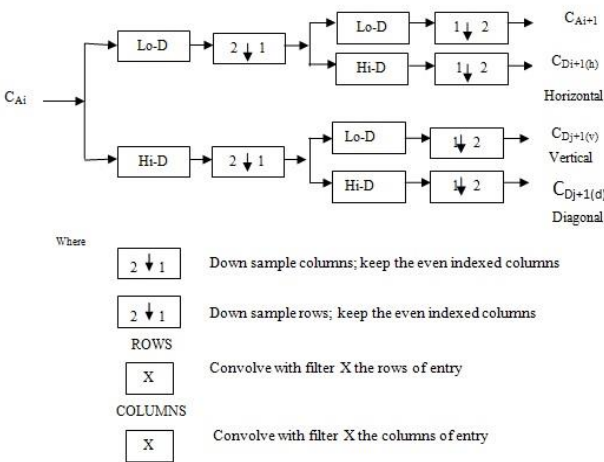


Fig. 1. Overview of the proposed method

A. Discrete Wavelet Transform

The wavelet transform provides a time-frequency representation of the signal. Thus wavelet transforms have become one of the most important and powerful tool of signal representation. Nowadays it has been used in image processing. They have been used for feature extraction, denoising, compression, face recognition, image super resolution. The discrete wavelet transform (DWT) is obtained by filtering the signal through a series of digital filters at different scales. The scaling operation is done by changing the resolution of the signal by the process subsampling. The DWT can be computed using either convolution-based or lifting-based procedures. In both methods, the input sequence is decomposed into low-pass and high-pass subbands, each consisting of half the number of samples in the original sequence.



Initialization $CA_0=S$ for decomposition initialization

Fig. 2. 2D-DWT Functional Process

Fig. 2. shows the functional process of 2D-DWT. Here 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. At each level in DWT, a 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. This operation results in four decomposed subband images referred to as low-low (LL), low-high (LH), high-low (HL), and high-high (HH) frequency sub-bands. Here the low pass filter is denoted by Lo-D and high pass filter is denoted by Hi-D. The frequency components of those sub-band images cover the frequency a component of the original image is shown in Fig. 3.

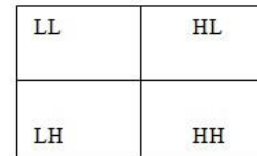


Fig. 3. Result of 2D-DWT

B. Dominant Brightness Level Analysis

An image must have the proper brightness and contrast for easy viewing. If the spatially varying intensity distributions are not considered the correspondingly contrast-enhanced images may have intensity distortion and lose image details in some regions. So for overcoming these two problems here we introduce a new contrast enhancement method for remote sensing images. The previous histogram based contrast enhancement techniques cannot preserve edge details exhibit saturation artifacts in low- and high-intensity regions. For overcoming these problems we decompose the input image into multiple layers of single dominant brightness levels. The illumination information is embedded in the LL subband then we perform illumination enhancement in the LL subband based on dominant brightness level analysis [6] using a log-average luminance function. So 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. The dominant brightness at the position (x, y) is computed as,

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

where S represents a rectangular region encompassing (x, y), L(x, y) represents the pixel intensity at (x, y), N_L represents the total number of pixels in S, ϵ and represents sufficiently small negative infinity. By using the above log-average luminance function here we map constant that prevents the log function from diverging to the middle grey of the displayed image, on a scale from zero to one. Thus the normalized dominant brightness varies from zero to one.

Thus in brightness level analysis the image is decomposed into low-, middle-, and high-intensity layers. The low-intensity layer has the dominant. 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 practical range of brightness is in between 0.5 and 0.6 in most images.

C. Adaptive Intensity Transformation

The optimal transfer function is calculated using the adaptive contrast enhancement. Here the adaptive intensity transfer function is generated based on the dominant brightness in each decomposed layer. 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 [11] and the gamma adjustment functions [12], [13]. 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.

Knee function slightly improves the highlight contrast by lowering the luminance in the middle range and knee transfer function stretches the low-intensity range by determining knee points. More specifically, single knee point is computed in the low- intensity layer as,

$$R_l = b_l + w_l(b_l - m_l) \quad (2)$$

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,

$$R_h = b_h - w_h(b_h - m_h) \quad (3)$$

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,

$$P_{ml} = b_l - w_m(b_{ml} - m_m) + (R_l - R_h) \quad (4)$$

$$P_{mh} = b_h + w_m(b_{mh} - m_m) + (R_l - R_h) \quad (5)$$

where w_m represents the tuning parameter and m_m represents the mean brightness in the middle-intensity layer.

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. This improves the visibility of details in dark and bright regions. The gamma adjustment function is modified from the original version by scaling and translation to incorporate the knee transfer function as,

$$G_k(L) = \left\{ \left(\frac{L}{M_k} \right)^{1/\gamma} - \left(1 - \frac{L}{M_k} \right)^{1/\gamma} + 1 \right\} \quad \text{for } k \in \{l, m, h\} \quad (6)$$

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 value is selected by computing maximum values of adaptive transfer function in ranges.

Three intensity transformed layers by using the adaptive intensity transfer function are fused; this layer is mainly used to make the resulting contrast-enhanced image in the wavelet

domain. After the enhancement using the intensity transformation function a weighting map estimation step is proposed here. In this step we extract most significant two bits from the low-, middle-, and high-intensity layers, then compute the sum of the two bit values in each layer, finally we select two weighting maps that have two largest sums. Here also a Gaussian boundary smoothing filter is applied for each intensity layers separately. Then finally the smoothed intensity layers are combined into one layer. This is the finally smoothed layer. So here Gaussian filter is used to remove the unnatural borders of fusion. As a result, the fused image F is estimated as,

$$F = W_1 \times c_l + (1 - W_1) \times \{W_2 \times C_m + (1 - W_2) \times c_h\} \quad (7)$$

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 (7) represents the point operation, the pixel coordinate (x, y) is omitted. The smoothed layer and weighting map estimated layer are combined into one layer. Then a fused image is obtained in the wavelet domain [14], this undergoes IDWT together with LL, LH, HH layer to get a fused 1st image. The contrast enhanced intensity layers [15] are combined into one layer, then LL subband is added into this layer. This fused in the wavelet domain undergoes IDWT together with LL,LH, HH layer to get a fused 2nd image. These two fused images are again combined into one to get an enhanced image.

D. Principle Component Analysis

Principal component analysis (PCA)[16] is one of the most widely implemented tools for dimensionality reduction or data exploration. It transforms a number of possibly correlated variables into a smaller number of new variables, known as principal components. Here PCA is used to minimize the error values in the enhanced image.

The detailed description of the stages in the proposed method is given in the block diagram shown in Fig. 4 .

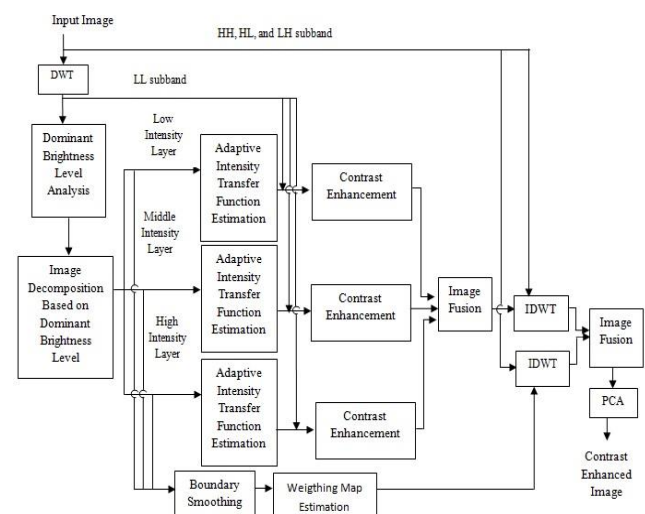


Fig. 4. Block diagram of the proposed method

III. RESULTS AND DISCUSSION

The following figures show the outputs of each step in this contrast enhanced method using remote sensing image.

A. Discrete Wavelet Transform

The input image is converted into grayscale image and Discrete Wavelet Transform (DWT) is used to decompose this image into different subbands as low-low (LL), low-high (LH), high-low (HL), and high- high (HH) frequency subbands. The illumination information is embedded in the LL sub band and the edges are concentrated in other subbands, hence separating the high frequency subbands, and applying the illumination enhancement in the LL subband only will protect the edge information from possible degradation. So the contrast enhancement performed only at this LL subband. Fig. 5 shows the input remote sensing image decomposed frequency bands using DWT.

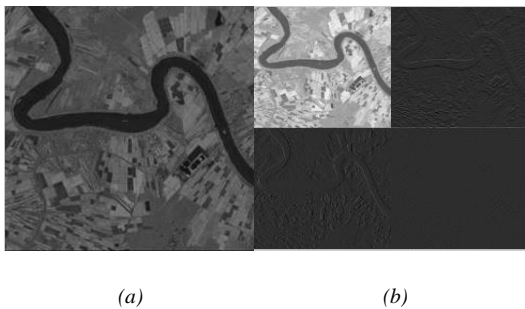


Fig. 5. Discrete Wavelet Transform in remote sensing image : (a) Input image (b) Decomposed subbands using DWT

B. Dominant Brightness Level Analysis

The main aim of this step is the decomposition of the input image into multiple layers of single dominant brightness levels. Here the approximate image in the LL subband is normalized using log average luminance function. In the resulting image dominant brightness varies from zero to one. Thus the image is decomposed into low, middle and high intensity layers based on their bound values. Here we used 0.4 and 0.7 for the low and high bounds, respectively. So the brightness level lower than this 0.4 value is considered as low intensity region, greater than 0.7 is considered as high intensity region and in between this range is considered as middle intensity region. The resultant image after intensity layer decomposition is shown in Fig. 6

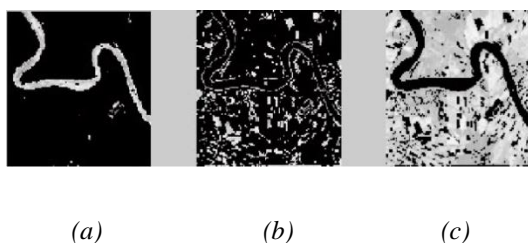


Fig. 6. Decomposed intensity layers: (a) low (b) middle (c) high

C. Adaptive Intensity Transformation

The optimal transfer function is calculated for each layer using knee transfer function, and gamma adjustment function. The knee transfer function is calculated by computing the knee points at each intensity layers and a gamma adjustment function is applied to this knee transfer image as discussed

earlier. The knee transfer function image has distorted details in the low- and high-intensity layers. The gamma adjustment function is applied to this knee transfer image to improve the visibility of details in dark and bright regions. The enhanced intensity layers after intensity transfer function is shown in Fig. 7.

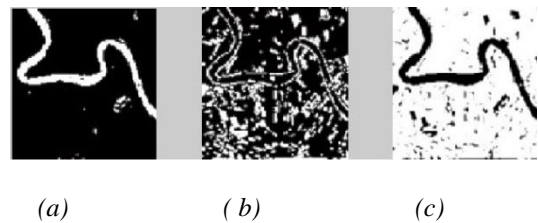


Fig. 7. Enhanced intensity layers: (a) low (b) middle (c) high

After the enhancement using the intensity transformation function the weighting map is estimated by calculating the largest weighting map from three intensity layers and by calculating the contrast enhanced brightness in three intensity layers. Here boundary smoothing is performed by using a Gaussian boundary smoothing filter also. Here this Gaussian boundary smoothing filter is applied for each decomposed intensity layers.

The Inverse DWT is performed for both the combined smoothed layer and weighting map estimated layer, and for combined contrast enhanced layers and LL subband layer together with the unprocessed HL, LH, and HH subbands then we get two images as shown in Fig. 8.



Fig. 8. Inverse DWT output

The output of IDWT is two combined images and these combined images are again combined to get a fused image. The fused image is given to Gaussian smoothing filter to remove unnatural borders of fusion.

D. Principle Component Analysis

The enhanced image after fusion from IDWT undergoes PCA to minimize the error values, then we get a highly contrast enhanced image. Then finally enhanced image is shown in Fig. 9.



Fig. 9. Enhanced image

IV. CONCLUSION

In this paper we presented an edge preserving contrast enhancement method using PCA in satellite images. The proposed algorithm decomposes the input image into four wavelet subbands and decomposes the LL subband into low-, middle-, and high-intensity layers by analysing 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 subbands. Then PCA is used to minimize the error values. The proposed algorithm can effectively enhance the overall quality and visibility of local details better than existing methods.

ACKNOWLEDGMENT

We would like to take this opportunity to express our gratitude to all those who have guided in the successful completion of this endeavor.

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. 18, Feb. 1997.
- [3] Y. Wan, Q. Chen, and B. M. Zhang, Image enhancement based on equal area dualistic sub-image histogram equalization method, *IEEE Trans. Consum. Electron.*, vol. 45, no. 1, pp. 6875, Feb. 1999.
- [4] S. Chen and A. Ramli, Contrast enhancement using recursive mean separate histogram equalization for scalable brightness preservation, *IEEE Trans. Consum. Electron.*, vol. 49, no. 4, pp. 13011309, Nov. 2003.
- [5] H. Demirel, C. Ozcinar, and G. Anbarjafari, Satellite image contrast enhancement using discrete wavelet transform and singular value decomposition, *IEEE Geosci. Remote Sens. Lett.*, vol. 7, no. 2, pp. 3333337, Apr. 2010.
- [6] 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 2013.
- [7] 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. 15.
- [8] E. Reinhard, M. Stark, P. Shirley, and J. Ferwerda, Photographic tone reproduction for digital images, in *Proc. SIGGRAPH Annu. Conf. Comput. Graph.*, Jul. 2002, pp. 249256.
- [9] L. Meylan and S. Susstrunk, High dynamic range image rendering with a retinex-based adaptive filter *IEEE Trans. Image Process.*, vol. 15, no. 9, pp. 28202830, Sep. 2006.
- [10] S. Chen and A. Beghdadi, Nature rendering of color image based on retinex, in *Proc. IEEE Int. Conf. Image Process.*, Nov. 2009, pp. 18131816.
- [11] Y. Monobe, H. Yamashita, T. Kurosawa, and H. Kotera, Dynamic range compression preserving local image contrast for digital video camera, *IEEE Trans. Consum. Electron.*, vol. 51, no. 1, pp. 110, Feb. 2005.
- [12] S. Lee, An efficient contrast-based image enhancement in the compressed domain using retinex theory, *IEEE Trans. Circuit Syst. Video Technol.*, vol. 17, no. 2, pp. 199213, Feb. 2007.
- [13] W. Ke, C. Chen, and C. Chiu, BiTA/SWCE: Image enhancement with bilateral tone adjustment and saliency weighted contrast enhancement, *IEEE Trans. Circuit Syst. Video Technol.*, vol. 21, no. 3, pp. 360364, Mar. 2010.

- [14] S. Kim, W. Kang, E. Lee, and J. Paik, Wavelet-domain color image enhancement using filtered directional bases and frequency-adaptive shrinkage, *IEEE Trans. Consum. Electron.*, vol. 56, no. 2, pp. 1063 1070, May 2010.
- [15] S. S. Agaian, B. Silver, and K. A. Panetta, Transform coefficient histogram based image enhancement algorithms using contrast entropy, *IEEE Trans. Image Process.*, vol. IP-16, no. 3, pp. 741758, Mar. 2007.
- [16] R. Vani, Dr. R. Soundararajan, DWT and PCA Based Image Enhancement with local Neighborhood filter Mask, *IOSR Journal of Computer Engineering (IOSRJCE)*, 2278-8727 Volume 9, Issue 2 (Jan. - Feb. 2013).

AUTHORS PROFILE

Sruthy M Sreedhar Completed B.Tech in Information Technology from Mahatma Gandhi University Kottayam, and completed M.Tech in Image Processing from Cochin University of Science and Technology.

Sarayu Vijayan currently working as Assistant Professor in Department of Computer Engineering at College of Engineering Chengannur Alappuzha.