Review of Image Enhancement Techniques for Remote Sensing Applications

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***Abstract*—The field of remote sensing and image processing are constantly evolving in the last decade. At present there are many enhancement techniques which are used for remote sensing image processing. The contrast of remote sensing images is low, which may include various types of noises. In order to make full use of remote sensing image information, the original image has to be enhanced. This paper presents different technologies which are recently proposed for remote sensing image processing. These techniques overcome the limitations of conventional methods. This represent enhancement methods based on Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Multi-Scale Retinex, Singular Value, Adaptive Intensity Transformations, and Dual-Tree Complex Wavelet Transform (DT-CWT). These methods overcome the limitations of the existing methods. Different application area has different requirement for image enhancement. These techniques perform image enhancement in different areas and have unique advantages in different image processing fields.**

***Index Terms*—Remote Sensing Images, Discrete Wavelet Transform (DWT), Multi-Scale Retinex, Dual-Tree Complex Wavelet Transform (DT-CWT), Adaptive Intensity Transformation.**

I. Introduction

For several decades, demands of remote sensing images are increasing. At present remote sensing images are used in many fields such as military, urban monitoring, change or target detection, geology, agriculture, aerospace, etc. Sometimes remote sensing image are unqualified because of limitations of existing imaging technology. As demand for remote sensing images rising, image enhancement techniques are required to exhibits more useful information from the source image.

There are many image enhancement methods which have been proposed by many researchers. Existing conventional methods have some limitations. Widely used method for image enhancement is Histogram equalization (HE) [1]. To overcome the limitations of the HE method, gain-controllable clipped HE (GC-CHE) has been proposed in [2]. GC-CHE controls the gain and performs clipped HE for preserving the brightness, which tends to distort image detail in low and high intensity regions. Another method which was used widely for Resolution Enhancement (RE) is interpolation [3]. Conventional RE method, which does not use DWT, suffers from the drawback of losing high-frequency contents, which results in blurring. Other classical methods have been proposed for contrast enhancement such as gain/offset correction, Nonlinear transforms [4]. However, these methods does not provide satisfactory enhancement for images taken under complex lighting conditions.

Many recent enhancement techniques have been proposed to overcome the limitations of traditional techniques. Some of the methods such as Contrast Enhancement using Dominant Brightness Level Analysis and Adaptive Intensity Transformation which uses DWT. Other methods which are discussed here are Dual-Tree Complex Wavelet Transform and Nonlocal Means, Multi-Scale Retinex, and Singular Value Decomposition.

II. The Framework of Remote Sensing Image Processing

From acquisition to the final enhanced output image, a remote sensing image goes under series of image processing steps. These image processing steps are divided into three main categories which are Transmission, Pre-processing and Processing. Transmission involves the coding strategy which is nothing but compressing for transmission. Pre-processing includes fusion, feature extraction and denoising. Processing step comprises unmixing, regression and classification. Each step is explained in detail in following sections.

A. Coding

Sensor technology which is being used to capture remote sensing images has been significantly developed, improving, among others, the spatial and spectral resolution. Such improvement on quality leads to an increasing demand on storage and bandwidth transmission capabilities. Both lossy and lossless image coding schemes have been investigated for remote sensing images. The lossy coding systems recommendation are based on a transform stage, where data is decorrelated in the spatial domain using a wavelet transform, thus following the latest standard JPEG2000 for grayscale images. Other well known wavelet-based coding system used are Set Partitioning In Hierarchical Trees (SPIHT) and Set Partioning Embedded Block Coder (SPECK). In order to improve the coding performance, a common strategy is to decorrelate first the image in the spectral domain.

B. Feature Extraction

When dealing with high dimensional datasets, such as hyperspectral images, the computational time is increased and the high collinearity and presence of noisy bands can degrade the quality of the model. Feature selection and extraction are main issues in these situations due to the curse of dimensionality. Although filter methods, such as the correlation or the mutual information between bands and class labels, have been extensively studied in remote sensing, the recent advances focus on wrappers, which select features that minimize the classification error. Support Vector Machine (SVM) based recursive feature elimination and genetic algorithms are some examples of recent successful applications of wrappers in remote sensing. Regarding feature extraction, the use of linear methods such as Principal Component Analysis (PCA) is quite common. Recently, advances in nonlinear methods for data description have been proposed such as locally linear embedding or isometric mapping. Also, multivariate kernel-based feature extraction methods have been presented recently to cope with nonlinearities in the data.

C. Restoration and Denoising

Image restoration is an important step in the image processing chain. Several problems are encountered in this application: different noise sources and amounts are present in the data and scattered either in the spatial or specific spectral bands. This makes necessary appropriate spatial smoothing per band. In addition, applying PCA captures second-order statistics only, and has no information about noise variance. An alternative is the widely used Minimum Noise Fraction (MNF) algorithm. In hyperspectral images the noise covariance estimation is a more challenging problem and other techniques have been recently proposed, such as anisotropic difussion, wavelet shrinkage, or kernel multivariate methods. In radar signal processing, the main problem is removing speckle noise in SAR images. Latest advances propose specific wavelet forms and to include spatial information through Markov random fields. Assessment of the obtained filtered images is another hot topic in this area. A common problem is also found in removing the registration noise, with critical impact in change detection applications.

D. Image Fusion and Enhacement

Spatial resolution of sensors is often limited with respect to their spectral resolution. Multi- or hyperspectral sensors give a unique amount of spectral information, but they often lack the spatial detail necessary for the application. On the contrary, panchromatic sensors provide information with higher level of spatial detail, but lack spectral information. Since the design of a high resolution sensor in both spectral and spatial domains would be extremely costly and challenging in terms of engineering, image fusion methods are often employed to create an image taking advantage of both panchromatic and multi- or hyperspectral sensors. IHS or PCA methods are inadequate when applied to remote sensing images. Therefore, specific approaches based on Laplacian Pyramids, wavelets, geostatistics, and Bayesian Maximum Entropy, have been proposed recently.

E. Signal Unmixing

An important problem in remote sensing is the development of automatic extraction of spectral endmembers directly from the input hyperspectral data set. With these pure pixels in the image identified, all pixels can be synthesized as a linear (or non-linear) combination of them, and this, in turn, allows subpixel detection or mineral mapping. Some classic techniques for this purpose include the N-finder (N-FINDR) algorithm, the Vertex Component Algorithm (VCA) in, and an Orthogonal Subspace Projection (OSP) technique in, among others. Selection of the free parameters and inclusion of spatial information in the unmixing process are key issues nowadays. Recently Support Vector Domain Description (SVDD) has been also used.

F. Regression and Model Inversion

In remote-sensing data analysis, the estimation of biophysical parameters is of special relevance in order to better understand the environment dynamics at local and global scales. The inversion of analytical models introduces a higher level of complexity, induces an important computational burden, and sensitivity to noise becomes an important issue. Consequently, the use of empirical models adjusted to learn the relationship between the acquired spectra and actual ground measurements has become very attractive. Parametric models have some important drawbacks, which typically lead to poor prediction results on unseen data. As a consequence, nonparametric and potentially non-linear regression techniques have been effectively introduced for the estimation of biophysical parameters from remotely sensed images. Different models and architectures of neural networks have been considered for the estimation of biophysical parameters. Recently the Support Vector Regression (SVR) method has been presented as an alternative for modeling some biophysical parameters.

G. Image Classification

In remote sensing image processing image classification is one of the most important aspects. Classification can be done based on applications of the remote sensing images. Important applications of the remote sensing images are urban monitoring, military field, geology, aerospace, change or target detection, etc. classification method can be divided in three main categories which are Unsupervised methods, Supervised method and Semi-supervised methods. Unsupervised method aim at clustering the image pixels into a pre-defined number of groups by measuring their similarity. One of the main applications of such method is change detection, where the method should be able to recognize changes in real time. Supervised methods use labeled information to train a model capable to recognize pre-defined classes. Recently, this field is probable the most active in remote sensing image processing. The most successful methods are neural networks and support vector machines. It was used in wide range of different domains, including object recognition and urban monitoring. Target and anomaly detection is also very active and kernel methods have been lately paid attention. Finally, Semi-supervised methods

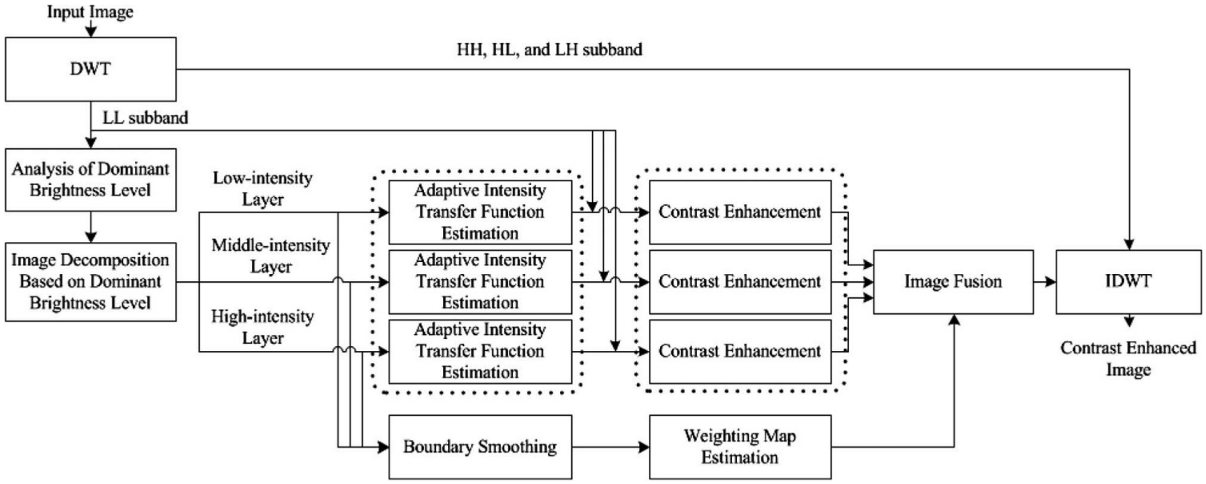

Fig. 1. Block diagram of method proposed in ref. [5].

exploit the information about the unlabeled samples to improve the performance of supervised methods. Thus classification is done based on the different application areas.

III. Recent Techniques

A. Dominant Brightness Level Analysis and Adaptive Intensity Transformation

There are many image enhancement techniques have been proposed for remote sensing applications. Some techniques use wavelet transforms such as Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT). Method in [5] which uses dominant brightness level analysis and intensity transform. This method first performs DWT for decomposition of the input image to get the set of band-limited components called LL, LH, HL and HH. LL subband has the illumination information, thus log-average luminance is computed in the LL subband for computing the dominant brightness level of the input image. The LL subband will be decomposed into low, middle and high intensity layer based on dominant brightness level. After decomposition of LL subband intensity transfer function is computed and applied. Intensity transfer function is computed in three layers using the dominant brightness level, the knee transfer function [6] and the gamma adjustment function [7]. Adaptive intensity transfer function is applied for color preserving and high quality contrast enhancement. At last, final enhanced image is obtained by applying inverse discrete wavelet transform (IDWT).

This method enhances the overall quality of the input image and visibility of local details. This enhances the low contrast remote sensing image and preserves the average brightness and edge details in all intensity ranges. This has unique advantage on the remote sensing images. Block diagram is as shown in Figure 1. Enhancement using the dominant brightness level analysis and adaptive intensity transformation shown in Figures 2 and 3. Figure 2 is the original image to be enhanced and Figure 3 shows the final enhanced output image.

Fig. 2. Original image to be enhanced.

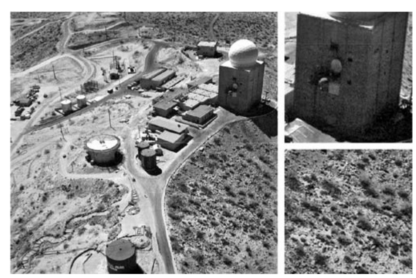

Fig. 3. Enahancement using method mentioned in [5].

This technique uses the DWT for decomposition and DWT is shift variant and this suffer from drawback of losing high-frequency contents which may results in blurring.

B. Multi-Scale Retinex Algorithm

Retinex theory was proposed by Edwin Land and McCann. The primary goal of retinex based enhancement algorithm is to decompose an image into a reflectance image and illumination image to remove the illumination effect. Many retinex-based image enhancement techniques have been proposed, their common principle is to assign a new value to each pixel in an image based on spatial comparisons of light intensities.

The current implementation of retinex algorithm was proposed by Hurlbert which enhances the image using of Gaussian surround function. Retinex theory was briefly described in [8]. The single-scale retinex (SSR) is given as follows.

$$R(x, y) = logI(x, y) - log[F(x, y) * I(x, y)] \quad (1)$$

Where, R(x,y) is enhancement output for the retinex. I(x,y) is an input image, * is convolution operator, F(x, y) denotes surround function which is given by following expression.

$$F(x, y) = K_{exp}[-(x^2 + y^2)/\sigma^2] \quad (2)$$

Where σ is Gaussian surround space constant, which is also known as scale parameter, K is coefficient.

The Multi-scale Retinex (MSR) can be given as a weighted combination of SSR. Mathematical expression is given as follows.

$$R_m(x, y) = \sum_{n=1}^{N} W_n[log[I_m(x, y)] - log[I_m(x, y) * F_n(x, y)]] \quad (3)$$

$m = 1, ..., k$

Where $R_m(x, y)$ is the output of the MSR, m represents the m^{th} spectral band, k is the number of spectral bands, k=1 represents gray-scale image, k=3 represents color image (RGB). W_n represents weight coefficients associated with F_n, n is the number of environmental functions, in which environmental function F_n select different standard deviation σ_n to control the environment function range of the scale. The expression is given as follows

$$F_n(x, y) = K_n exp[-(x^2 + y^2)/\sigma_n^2] \quad (4)$$

Where σ_n is scale parameter for the first n-surround function. Coefficient K_n to be met:

$$\int\int K_n exp[-(x^2 + y^2)/\sigma_n^2]dxdy = 1 \quad (5)$$

Better self-adaptability can be achieved for MSR scale through the combination of multi measure, also it can achieve image adjustment under dynamic scope, which produces the enhanced output of the image. MSR was operated to the selected image with specific pixel resolution, which gives satisfactory results on remote sensing images. One example of image enhancement by this MSR method in [8] is shown in Figures 4 and 5.

Multi-scale retinex gives good quality image. As shown in above example it can achieve good visual effects with MSR method, but if want to achieve the best possible enhancement effect requires multiple iterations and to achieve the effect of Figure 5 it needs to iterate 80 times. It demands lot more iterations in color images to achieve good visual effects.

C. Dual-Tree Complex Wavelet Transform and Nonlocal Means

There are many resolution enhancement schemes have been proposed using wavelet transforms. Most widely used is discrete wavelet transforms (DWT). DWT suffer from some drawback like losing high frequency contents because DWT is a shift-variant. To overcome limitations of the DWT another transform, dual-tree complex wavelet transform (DT-CWT) proposed recently.

Fig. 4. Original image to be enhanced.

Fig. 5. MSR output image using method mentioned in [8].

Technique which was used for resolution enhancement (RE) of the satellite images in [9] uses DT-CWT. It performs resolution enhancement based on DT-CWT, Lanczos interpolation and NLM. DT-CWT which is nearly shift invariant and directional selective. DT-CWT gives promising results after the modification of the wavelet coefficients and gives less artifacts, as compared with DWT. Lanczos filter offer less aliasing, sharpness, and minimal ringing, therefore it is a good choice for resolution enhancement. The NLM filter which is an extension of the neighborhood filtering and it is based on the assumption that image content is likely to repeat itself within some neighborhood and in neighboring frames. NLM filtering [10] is used to further enhance the performance of DT-CWT by reducing the artifacts. Technique which is proposed in [9] which enhances the remote sensing images by performing the decomposition of low resolution input image using Dual-Tree Complex Wavelet Transform (DT-CWT). Wavelet coefficients and the LR input image were interpolated using the Lanczos interpolator. NLM filtering is used to overcome the artifacts generated by DT-CWT and to further enhance the performance to the proposed technique.

D. Singular Value and Discrete Wavelet Transform

Image resolution enhancement and contrast enhancement of the remote sensing images is constantly growing field. Many enhancement methods have been proposed using DWT which produces down sampling output which causes information loss in subbands. To overcome this limitation of the DWT another recent transform, Stationary Wavelet Transform (SWT) proposed which does not use down sampling but it is similar to DWT. Technique proposed in [11] which uses SWT and DWT. In this method low resolution and low contrast image is given as input to the SWT and DWT. Before applying image to the DWT, image is equalized using well known technique General Histogram Equalization (GHE). DWT is used to increase the quality of the input image and preserve the edges. Image decomposition is applied using the DWT, which decompose the image at first level. DWT decompose the image into to four different subband called LL, LH, HL and HH. The subband images are interpolated by using bicubic interpolation technique. DWT uses down sampling which cause the loss on its high frequency components. Hence SWT is used in [11] to minimize this loss.

In order to enhance the contrast and preserve the information in high frequency subband, Singular Value Decomposition (SVD) is used to the interpolated LL of DWT and SWT to produce a singular value matrix by the following equations.

$$LL_X = U_{LLX}\Sigma_{LLX}V_{LLX}^T \tag{6}$$

$$LL_Y = U_{LLY}\Sigma_{LLY}V_{LLY}^T \tag{7}$$

Where LL_X and LL_Y are singular value matrix of SWT and DWT respectively. U_{LLX} and U_{LLY} are the orthogonal matrix, V_{LLX}^T and V_{LLY}^T are the orthogonal transpose matrix, Σ_{LLX} and Σ_{LLY} are the singular value on the main diagonal which contains the intensity information of the given image. The new coefficient of the singular value matrix calculated by following equation.

$$\zeta = \frac{max\Sigma_{LL_Y}}{max\Sigma_{LL_X}} \tag{8}$$

Where Σ_{LL_Y} and Σ_{LL_X} are the LL singular value matrix of the DWT and SWT input image respectively. The new LL image is obtained by following equation.

$$\overline{\Sigma LL_X} = \zeta\Sigma LL_X \tag{9}$$

$$\overline{LL_X} = U_{LL_X}\overline{\Sigma LL_X}V_{LL_X} \tag{10}$$

New corrected high frequency subbands and reconstructed $\overline{LL_X}$ are interpolated by specific enlargement factor. Now $\overline{LL_X}$ and estimated LH, HL and HH subband images are combined by applying IDWT to generate the enhanced image. The output of the IDWT will have sharper edges with good contrast and resolution. Enhancement using this method is shown in Figures 6 and 7. Figure 6 is an original image and Figure 7 is the output image.

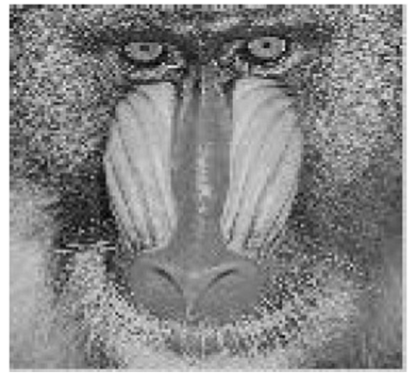

Fig. 6. Original input image.

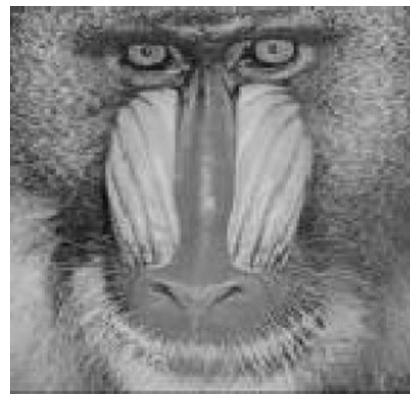

Fig. 7. Output image using method mentioned in [11].

There are two main advantages of using SVD. First, the singular value matrix obtained by SVD contains the illumination information. So, changing the singular values will affect the illumination of the image and other information remains unchanged. Second, by applying the illumination enhancement in LL subband will protect the edge information in other subbands. One disadvantage of this method is, if the contrast of the image is highly concentrated on a specific range, the information may be lost in those area which are uniformly concentrated.

IV. Conclusion

For several decades, remote sensing images have played an important role in many different application areas. As the rising demand for high-quality remote sensing images, contrast enhancement techniques are required for better visual perception and color reproduction. Based on different application requirement, we need different enhancement model and solutions. This paper presents a survey of image enhancement techniques for remote sensing images which are recently proposed for different application areas. This paper highlights the different image enhancement methods which are recently developed and it also highlights the advances of these methods in remote sensing image processing field. Conventional methods for image enhancement had many limitations. Methods which are reviewd in this paper shows how advantageous these methods are over the conventional methods. However different enhancement technique has unique advantage in different application area.

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