International Journal of Scientific & Engineering Research, Volume 8, Issue 5, May-2017
ISSN 2229-5518

Resolution enhancement of low resolution satellite images using Dual tree complex wavelet transform

M. HemaLatha Dr.S.Vardarajan

Abstract— In this research paper, a complex wavelet-domain image resolution enhancement algorithm is proposed based on the estimation of wavelet coefficients. In this method, dual tree complex wavelet transform is applied to low resolution (LR) satellite image. The method uses dual-tree complex wavelet transform and inverse dual-tree complex wavelet transform to get high resolution image from low resolution image. The set of wavelet coefficients is estimated from the DT-CWT decomposition through the rough estimation of the high resolution (HR) image. Then inverse dual tree complex transform is applied. Output is high resolution of satellite image. Image enhancement is used for the images which has lack of contrast and brightness. DT-CWT technique is applied on NOAA-19-HRPT satellite portraits and compared with DWT technique. The quantitative PSNR, RMSE, CC, and SSIM are calculated for satellite portraits. DT-CWT has better performance compared to DWT in all aspects.

Index Terms— Discrete wavelet transform (DWT), dual-tree complex wavelet transform (DT-CWT), High Resolution (HR), NOAA-19-HRPT.

1 Introduction

A digital portrait is indicated by means of a multitude with completely spaced and very little limited samples of the image. Digital portrait is composed of finite number of equal areas or picture elements (pixels or pels), each of which has particular value. Image is represented in grid fashion known as matrix. It has some values, which are signatures from various objects on the earth. Signatures are reflectances from various objects. Image processing is among rapidly growing technology with its applications in various applications. To improve the quality of image some pre-processing is done. Pre-processing eliminates noise in the satellite portraits. Pre-processing includes resizing, noise removal, filtering, and feature extraction. Pre-processing is done with the help of some software's like ERDAS.

Whenever antenna predicts the satellite, it receives information and gives the control room through cable. Satellite data comes in bits and bytes. Data is in raw format, which is called level 1B format. Raw data is in BIP (Band interleaved by line) format. Data is send to frames for synchronization and then sent to buffers for storing information. Finally data is send to computer. Raw data is converted into 1 bit format.

Spatial representation is nothing but pixels in time domain (2D) utilized in the construction of digital image. In time domain the analysis is difficult so we have to convert it in to frequency domain. Human being can understand the time domain, so again inverse of frequency domain or transform is applied. To accomplish this we use Fourier transform or different wavelet transforms and their inverse transforms.

Resolutions are of four type's namely spatial, spectral, radiometric and temporal resolution. Spatial resolution defines the clarity of the picture. For 30m resolution the clarity is less and for 1m resolution the clarity is more. The satellite gives more clarity about any building in that area, if it is 1m resolution. Spectral resolution defines spectral features and number of bands in different types of spectral images. For example panchromatic images are black and white with single band. A multispectral image has 2 or more bands i.e., R, G, and B. Hyper spectral images have 3 to 11 bands. Radiometric resolution defines digital number captured by sensor reflectance values of different targets on the earth. Different object gives different signatures, which is some digital value of the image. Temporal resolution defines same area covered by satellite at different times. In [1] and [2] the author explained about histogram equalization of image enhancement. 512× 512 image is represented by 9 bit. 8 bit image represents 256 grey levels [3].

Fourier transform has good frequency localization and poor time localization. STFT has good time and frequency localization. STFT has good frequency resolution at L.F's and good time resolution at H.F'S. Window size is fixed, which a major drawback. Wavelets have very good frequency localization and time localization. Wavelet analysis detects the time varying frequency components in non-stationary signals with required resolution detected temporal behavior. Wavelets give better spatial resolution compared to other transforms.

In this research paper, a dual tree complex wavelet transform based image enhancement technique is proposed which is shift and rotation invariant. DT-CWT is highly directional. There is no shift sensitivity and absence of phase in DT-CWT. When image is enhanced there is a loss of high frequency components, which is a major drawback. So DWT is used to retain the high frequency components. DWT is shift and rotation variant, shift sensitive, and there is an absence of phase. Because of these disadvantages there are discontinuities in neighborhood pixels, which lead to generation of artifacts. To avoid all these disadvantages DT-CWT is used.

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2 Study Area And Data Sets

Our study area has central longitude and latitude as 15.9129° N and 79.7400° E. The area covers major state Andhra Pradesh in India. The average high temperature is +48 ^{0}C. The NOAA- 19- HRPT has swath of 2,800km and swath angle of 55^0.NOAA is operated at 1.708 GHz (L-band) which has low resolution images. Our data has following characteristics. It gives low resolution data. An optical sensor on satellite converts information into digital. Information is in the form of packets, which is send to earth. NOAA has two visible and one IR channels. 1st, 2nd channels are operated in visible and 3rd is operated in IR. Two visible channels are used for finding vegetation index and one IR channel is used for finding temperature profiles.

Table 1: High resolution picture transmission (HRPT)

Resolution	1km
Data rate	665.4Kbps
Reception	L Band

Table 2: Characteristics of NOAA- 19- HRPT satellite

Operating wavelength	0.58-12.5 μm (6 bands)
Bands	20 bands
Datum	WGS 84
Resolution	1km
Date of acquiring	22-09-2016
Data format	Geo Tiff
Repeat cycle	Daily
Orbit type	Sun synchronous
Orbit height	870 km

3 Dwt

The decimated DWT has been widely used for image resolution enhancement [4],[5],[6]. A common hypothesis of DWT-based image resolution enhancement is that the low-resolution (LR) image is the low-pass-filtered sub band of the wavelet-transformed high-resolution (HR) image. This type of approach requires the evaluation of wavelet coefficients in sub bands containing high-pass spatial frequency information in order to estimate the HR image from the LR image.

Image resolution enhancement is very important factor in satellite image processing. The techniques in the image domain use the statistical and geometric data directly extracted from the input image itself [7], [8], while transform-domain techniques use transformations such as decimated discrete wavelet transform(DWT) to achieve the image resolution enhancement [7],[8],[9],[10].

In order to estimate the high-pass spatial frequency information, many different approaches have been introduced. In [11] and [12], only the high-pass coefficients with considerable magnitudes are anticipated as the evolution of the wavelet coefficients among the scales. The performance is mainly affected from the fact that the signs of the estimated coefficients are copied directly from parent coefficients without any attempt being made to estimate the actual signs. This is contradictory to the fact that there is very little correlation between the signs of the parent coefficients and their descendants. As a consequence the signs of the coefficients estimated using extreme evolution techniques cannot be relied upon. A hidden Markov tree (HMT)-based method in [11] models the unknown wavelet coefficients as belonging to mixed Gaussian distributions which are symmetrical about the zero mean. HMT models are used to determine the most probable state for the coefficients to be estimated. The performance also suffers mainly from the sign changes between the scales.

In modified DWT, the low resolution image of size m×n is applied which decomposes the image into 4 sub-bands (SB 'S). The HF sub-bands are interpolated using bi-cubic interpolation with a factor 2. The LF sub-band is interpolated by using same bi-cubic interpolation with a factor 2. The interpolated image is subtracted from original low resolution image whose output is difference image [16]. The difference image is added to all the high frequency sub-bands. All these HF sub-bands are interpolated by a factor $\alpha/2$ with bi-cubic. The original low frequency image is also interpolated by a factor $\alpha/2$ with bi-cubic. Finally inverse DWT is applied to get the high resolution image $\alpha m \times \alpha n$ as shown in Fig.1.

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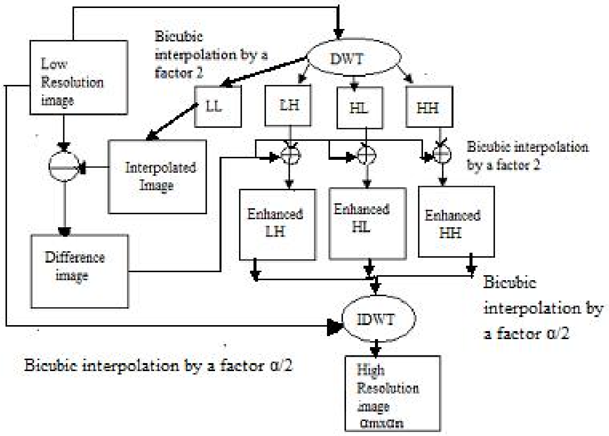

Fig.1. Bock diagram of DWT

The decimated DWT is shift variant and due to the suppression of wavelet coefficients discontinuities are introduced in the neighborhood pixels, which is known as ringing[10].The limitations of decimated DWT are fulfilled by Dual -tree complex wavelet transforms [9]. DT-CWT is shift invariant and has improved directional resolution when compared with that of the decimated DWT. So DT-CWT is used for image resolution enhancement.

4 DT-CWT

When two real-valued decimated DWTs are combined DT-CWT is obtained. The DWT is shift variant because of decimation operation performed. As a result, a small shift in the input signal can result in a very different set of wavelet coefficients .In Kingsbury [9] introduced a new wavelet transform is introduced called DT-CWT, which is shift invariant. DT-CWT has high directionality compared to DWT. Such features make DT-CWT more suitable for image enhancement and image denoising [15].

The Discrete Wavelet Transform (DWT) has been widely used in image processing for many applications. DWT gives “checker board” pattern, where data orientation analysis is not possible even though it has complete invertible transform of an image. DWT is not suitable for calculating invariant features because it is shift variant. To avoid these two major problems created by DWT, Freeman and Adelson first discussed about Steerable filters [13], which can be used to decompose an image into a Steerable Pyramid, by means of the Steerable Pyramid Transform (SPT) [14]. But SPT has also major drawback of designing filter and imperfect reconstruction and poor computational efficiency. In advancement of SPT, energy response can be achieved by the use of Hilbert pair of filters with Complex Wavelet Transform (CWT) [9]. Similarly to the SPT, in order to retain the whole Fourier spectrum, the transform needs to be over-complete by a factor of 4, i.e. there are 3 complex coefficients for each real one. Therefore, Kingsbury also introduced the Dual-tree Complex Wavelet Transform (DTCWT), which is shift invariant, rotation invariant and gives perfect reconstruction of any image.

- *M. HemaLatha is currently pursuing Ph.D degree program in electronics and communication engineering in Sri Venkateswara University,Tirupati, A.P, India,PH-9440939343. E-mail: maddihemalatha@gmail.com.*
- *Dr.S.Vardarajan is currently professor in electronics and communication engineering, Tirupati, A.P, India, PH-9959999636. E-mail:varadasouri@mail.com*

The high-pass coefficients, together with the LR image, are used to reconstruct the HR image using inverse DT-CWT (IDT-CWT).

5 METHODS AND RESULTS

In this research paper, a low resolution image as shown in Fig.2 is enhanced to high resolution images by using DWT, and DT-CWT techniques as shown in Fig.3, and Fig.4 respectively. Here wavelet techniques are implemented using MATLAB software. Peak signal-to-noise ratio (PSNR), Root mean square error (RMSE), correlation coefficient (CC), and Structural similarity index measurement (SSIM) are calculated for high resolution NOAA-19-HRPT image using DWT, and DT-CWT. The DT-CWT has given better performance in PSNR, RMSE, CC and SSIM compared to DWT as shown in TABLE 3. Fig.5 shows the comparison of SSIM and CC for DWT and DT-CWT techniques. DT-CWT has good PSNR value of 52.3356 and RMSE value of 0.6187. The image brightness and contrast has been increased by using DT-CWT.

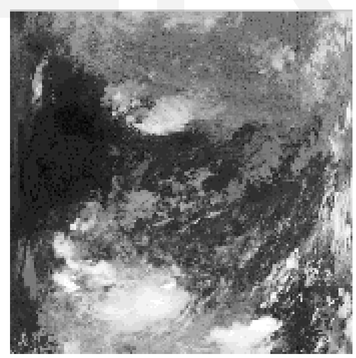

Fig.2. Low resolution satellite image

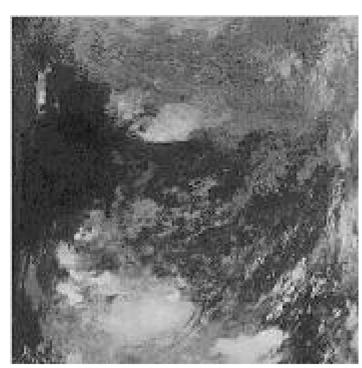

Fig.3. Resolution enhanced by DWT

International Journal of Scientific & Engineering Research, Volume 8, Issue 5, May-2017
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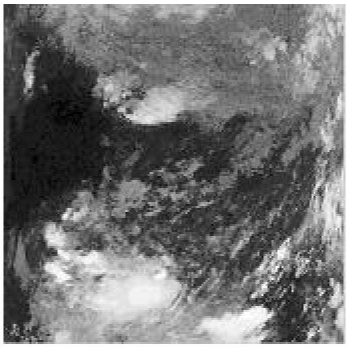

Fig.4. Resolution enhanced by DT-CWT

Table 3: Enhancement using DWT and DT-CWT techniques

ALGORITHM	***PSNR***	***RMSE***	***CC***	***SSIM***
DWT	44.8375	1.412	0.7457	0.2595
DT-CWT	52.3356	0.6187	0.9998	0.9985

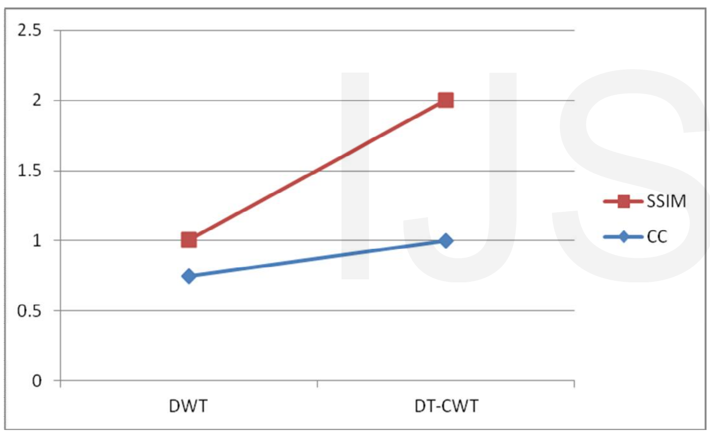

Fig.5. Comparison of SSIM and CC values for DWT and DT-CWT

6 Conclusion

Image resolution enhancement of LR image using the dual-tree complex wavelet transform is presented. Dual tree complex wavelet transform is applied to low resolution (LR) satellite image. The high resolution (HR) image is reconstructed from the low resolution image, together with a set of wavelet coefficients, using the inverse DT-CWT. Then inverse dual tree complex transform is taken. Output is high resolution image. The DT-CWT has better performance in PSNR, RMSE, CC, & SSIM compared to DWT technique.

Acknowledgment

The authors wish to thank C.O.E Lab, S.V.University for providing NOAA-19-HRPT, L-Band satellite images for research purpose.

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