International Journal For Technological Research In Engineering
Volume 1, Issue 6, February-2014 *ISSN (Online): 2347 - 4718*

A QUALITATIVE RESOLUTION ENHANCEMENT FOR SATELLITE IMAGE USING DUAL TREE COMPLEX WAVELET TRANSFORM

M. Vanitha[1], S. Castro[2], Dr. C. Kumar Charlie Paul[3]
Department of Computer Science, Anna University Chennai.
A.S.L Paul's College of Engineering & Technology, Coimbatore, India.

Abstract: This article proposes a novel method for enhancing of low contrast satellite digital images. Low contrast and poor quality are main problems in the production of Satellite images. By using the Dual tree complex wavelet transforms and flowed by using the lancoz interpolation then the NLM operator to obtain the RE image. First, a Satellite image was decomposed with wavelet transform. Secondly, all high-frequency sub bands were interpolated by lancoz interpolation. Thirdly, reduce the noise using Nlm operator. Finally, the RE image was obtained through the IDTCWT. The resulting image is then subtracted from the original image. Experiments shows that this method not only enhances an image's details but can also preserve its edge features effectively.

Keywords: DTCWT, Lancoz interpolation, NLM filtering.

I. INTRODUCTION

Conventional image resolution enhancement methods, like as bilinear and bicubic interpolation methods, provides wrong details and blurry output images as they do not utilize any information relevant to edges in the original image. Wavelet-based methods [1]-[8] enhanced the image resolution by estimating the preserved high frequency information from the given images. They were based on the assumption that the image to be enhanced was the low-frequency sub band among wavelet-transformed sub bands of the original one and the target is judge the high frequency sub images of wavelet transform, so can obtain the RE image. In in-band scalable video coding [10]-[13], because the motion estimation is performed in wavelet domain, over-complete form [9][10][12] of reference bands is usually used to solve the shift-variance problem in wavelet domain. However, it brings serious drifting errors in decoder since the high-frequency bands are not available to construct the over-complete form of reference band and the drifting error propagates along the lifting structure of temporal filtering. If the unavailable high-frequency bands are estimated from the only available low-frequency band in the coder, the drifting error will be reduced. So, wavelet RE technique becomes more and more important. In [1] and [2], the coefficients of high-frequency bands are estimated by exploiting the regularity of edges across scales. In these methods, only coefficients having significant magnitude can be estimated whereas it is difficult to estimate the other small coefficients. In [3] and [4], the statistical relationship between coefficients at lower level is modeled by using a hidden Markov model [5] to predict coefficients at high level. A set of parameters should be obtained from the training images, where the information from the training images may not match effectively with the input image. Cycle-spinning based resolution enhancement methods were also proposed recently in [6] and [7], where the ringing artifacts caused by decimation were eliminated by averaging out the translated zero-padded reconstruction images, and by using the local edge orientation to influence cycle spinning parameters. In [8], the unknown wavelet coefficients are estimated by utilizing existing correlation between neighboring coefficients. However, the correlation of the undecimated sub bands is not similar to the correlation of the eliminate sub images. Existing methods preserve the high-frequency bands directly from the available low-frequency band. DT-CWT-based nonlocal-means-based RE (DT-CWT-NLM-RE) technique is proposed, using the DT-CWT, Lanczos interpolation, and NLM. Note that DT-CWT is nearly shift invariant and choose the directional. DT-CWT saves the usual details of perfect reconstruction with well-balanced frequency responses [13], [14].Consequentially, DT-CWT gives promising results after the modification of the wavelet coefficients and provides reduce artifacts, as compared with traditional DWT. Since the Lanczosfilter provides sharpness, low aliasing, and effect of the ringness is minimum. NLM filtering [15] is used to further enhance the performance of DT-CWT-NLM-RE by reducing the artifacts

II. DTCWT

It is also an efficient technique to obtain a resolution enhance image. DT-CWT is applied to decompose a low resolution input image into different sub band images. In this technique, direction selective filters are used to generate high-frequency sub images, whereas filters show peak magnitude responses in the presence of image features oriented at angle +75, +45, +15, -15, -45and -75 degrees, respectively. Then the interpolated with six complex-valued images. The two images (sale up) are provided by interpolating the less resolution original input image and the shifted version of the input image in horizontal and vertical directions. These two real valued sub band images are used as the real and imaginary components of the interpolated complex LL image, respectively, for the IDT-CWT operation. Finally IDT-CWT is used to combine all these images to produce resolution enhanced image. In this contribution, we characterize the dual-tree transform from a complementary perspective by formally linking the multiresolution framework of wavelets with the amplitude-phase representation of Fburier analysis. The latter provides an efficient way of encoding the relative location of information in signals through the phase function that has a straightforward interpretation. Specifically, consider the Fourier expansion of a finite-energy signal *f(x)* on [0, *L]:*

$$f(x) = a_0 + a_1 \cos(\omega_0 x) + a_2 \cos(2\omega_0 x) + \cdots + b_1 \sin(\omega_0 x) + b_2 \sin(2\omega_0 x) + \cdots . \quad (1)$$

Here w_o ($w_o L = 2\pi$) denotes the fundamental frequency, and a_o, a_l, a_2, ..., and b_1, b2, ... are the (real) Fourier coefficients corresponding to the even and odd harmonics respectively. Now, by introducing the complex Fourier coefficients o_n = a, - jb_O and by expressing them in the polar form c_n = a_n -jb_n and by expressing in the polar from $c_{n=|Cn|}$ e jφn 0< φn<2π can be rewrite as (1)

$$f(x) = \sum_{n=0}^{\infty} |c_n| \left(\cos\phi_n \cos(n\omega_0 x) - \sin\phi_n \sin(n\omega_0 x) \right) = \sum_{n=0}^{\infty} |c_n| \varphi_n \left(x + \acute{\tau}_n \right) \quad (2)$$

With fn= φn /nwo specifying the displacement of the reference sinusoid φn(x) = cos(nwox) relative to its fundamental period [0, *L/n]*. The above amplitude-phase representation highlights a fundamental attribute of the shift parameter fn it corresponds to the shift I that maximizes $|\langle f(\cdot), \varphi_n(\cdot + \acute{\tau}) \rangle|$, the correlation of the signal with the reference $\varphi_n(x)$. The corresponding amplitude |cn| measures the strength of the correlation

III. LANCOZ INTERPOLATION

Lanczos Resampling uses a convolution kernel to resample unknown data in a scaled picture. When a picture has been measured, points between the correct pixels will be interpolated. The interpolation consists of weighting the original pixels influence on the new pixel. The weights are relates to the location of the new pixel, and are found by the Lanczos algorithm.

$$L(x) = \begin{cases} \operatorname{sinc}(x)\operatorname{sinc}\left(\frac{x}{a}\right) & -a < x < a, x \neq 0 \\ 1 & x = 0 \\ 0 & \text{otherwise} \end{cases} \quad \text{-- (3)}$$

The formula uses the normalized function. The varying x is determined as the length an original pixel from the actual pixel in the scaled picture. It is not defined at x = 0, we define it as 1 because if the distance from the new measured pixel, to the measured original pixel is 0, the pixel should be weighed 100%.When implementing the resampling technique the size of the convolution kernel is dependent on a value beta, it represents how to pixels will influence the new pixel value, in each direction. The alpha value squared with the scale factor equals the size of half the kernel in single dimension. In implement only one half the kernel is need because, the output of the Lanczos interpolation is symmetrical over the y axis. Since the beta value itself is defined to 0 if put through the Lanczos algorithm, one entry can be subtracted from the half-kernel size. If a picture is measured by 3, each empty pixel will have a distance of 1/3 to the nearest original pixel, and 2/3's to the second nearest

IV. NON LOCAL MEANS

The NLM filter (an extension of neighborhood filtering algorithms) is based on the assumption that image content is probably to repetition itself within some nearest (in the image)[15] and in neighboring frames [16]. It computes denoised pixel x (p,q) by the weighted sum of the surrounding pixels of Y (p,q)

$$x(p,q) = \frac{\sum_{m=1}^{M} \sum_{(r,s)\in N(p,q)} Y_m(r,s) K_m(r,s)}{\sum_{m=1}^{M} \sum_{(r,s)\in N(p,q)} K_m(r,s)} \quad \text{-- (4)}$$

That feature provides a way to estimate the pixel value from noise fouled images. In a 3-D NLM method, the measure of a pixel at position (p,q) is where m is the frame index, and N represents the nearest of the pixel at location (p,q) . K values are the filter weights

$$K(r,s) = \exp\left\{ -\frac{\|V(p,q) - V(r,s)\|_2^2}{2\sigma^2} \right\} \times f\left(\sqrt{(p-r)^2 + (q-s)^2 + (m-1)^2} \right) \quad \text{-- (5)}$$

where V is the window [usually a square window centered at the pixels Y (p,q) and Y (r, s)] of pixel values from a geometric neighborhood of pixels Y (p,q) and Y (r, s) , σ is the filter coefficient, and f (x) is a geometric function. K is inversely proportional to the distance between Y (p,q) and Y(r,s).

V. PROPOSED TECHNIQUE

The proposed technique is used to overcome the major drawbacks of DWT; we use Dual tree complex wavelet transform, interpolation and NLM filtering. In Dual tree complex wavelet transform, more number of frequency sub bands are obtained, then the images are processed using interpolation and NLM filtering. Lanczos filter is a mathematical interpretation and it is used to smoothly interpolate the value of a digital signal between its sample signals. Interpolation is the process of determining the values of a function at positions lying between its sample signals. It achieves this process by suitable a continuous function through the discrete input samples. This allows input values to be evaluated at arbitrary positions in the input, not just those defined at the sample signal points. Band limited, interpolation plays an opposite role: it reduces the bandwidth of a signal by applying a low-pass filter to the discrete signal. That is, interpolation reconstructs the signal lost in the sampling process by smoothing the data samples with an interpolation function. The non-local means algorithm does not make the same assumptions about the image as other methods. Instead it assumes the multichannel image contains an extensive amount of self-similarity. Eros and Leung originally developed the concept of self-similarity for texture synthesis. The self-similarity assumption can be exploited to denoise an image. Pixels with similar neighborhoods can be used to determine the denoised value of a pixel.

VI. RESULT AND DISCUSSION

During simulation different modules are processed and its results are shown below. Also its PSNR values and MSE values are calculated and tabulated. Following are the results of DT-CWT technique, which includes the process of Lancoz interpolation and non-local means filtering. Comparison results of DWT, DT-CWT without NLM and DT-CWT with NLM Peak signal to noise ratio is calculated for all the algorithms and tabulated below.

S.no	Algorithm	PSNR (db)	MSE
1	DWT -RE	13.7802	0.0464
2	SWT-RE	14.1202	0.0419
3	Lancoz-RE	15.3204	0.0253
4	DT-CWT Without NLM	33.2051	0.3025
5	DT-CWT With NLM	36.5373	0.3513

Table 1: compare MSE, PSNR values of different techniques

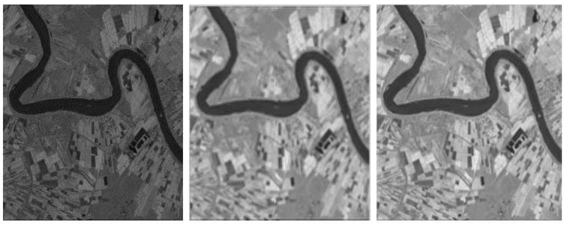

Fig 1(i) (ii) (iii)

(I) input image (ii) DWT-RE Method (iii) Proposed Method

VII. CONCLUSION

This method has proposed a new RE technique based on the lancoz interpolation and NLM filtering of the high-frequency sub band images obtained by DTCWT and the input image. This technique has been tested on standard benchmark images, and their MSE and PSNR and visual results show the higher ranking of the proposed technique over the existing and state-of-art image RE techniques.

REFERENCES

[1] [Online].Available:http://www.satimagingcorp.com/
[2] Y. Piao, I. Shin, and H. W. Park, "Image resolution enhancement usinginter-subband correlation in wavelet domain," in Proc. Int. Conf. Image Process., San Antonio, TX, 2007, pp. I-445–I-448.
[3] C. B. Atkins, C. A. Bouman, and J. P. Allebach, "Optimal image scaling using pixel classification," in Proc. Int. Conf. Image Process. , Oct. 7–10, 2001, pp. 864–867.
[4] A. S. Glassner, K. Turkowski, and S. Gabriel, "Filters for common resampling tasks," in Graphics Gems. New York: Academic, 1990, pp. 147–165.
[5] D. Tschumperle and R. Deriche, "Vector-valued image regularization with PDE's: A common framework for different applications," IEEE Trans. Pattern Anal. Mach. Intell. , vol. 27, no. 4, pp. 506–517, Apr. 2005.
[6] M. J. Fadili, J. Starck, and F. Murtagh, "In painting and zooming using sparse representations," Comput. J., vol. 52, no. 1, pp. 64–79, Jan. 2009.
[7] H. Demirel and G. Anbarjafari, "Discrete wavelet transform-based satel-lite image resolution enhancement," IEEE Trans. Geosci. Remote Sens., vol. 49, no. 6, pp. 1997–2004, Jun. 2011.
[8] H. Demirel and G. Anbarjafari, "Image resolution enhancement by using discrete and stationary wavelet decomposition," IEEE Trans. Image Pro-cess. , vol. 20, no. 5, pp. 1458–1460, May 2011.
[9] H. Demirel and G. Anbarjafari, "Satellite image resolution enhancement using complex wavelet transform," IEEE Geosci. Remote Sens. Lett. , vol. 7, no. 1, pp. 123–126, Jan. 2010.
[10] H. Demirel and G. Anbarjafari, "Image super resolution based on interpolation of wavelet domain high frequency sub bands and the spatial domain input image," ETRI J., vol. 32, no. 3, pp. 390–394, Jan. 2010.
[11] H. Zheng, A. Bouzerdoum, and S. L. Phung, "Wavelet based non-local-means super-resolution for video sequences," inProc. IEEE 17th Int.
[12] A. Gambardella and M. Migliaccio, "On the super resolution of microwave scanning radiometer measurements," IEEE Geosci. Remote Sens. Lett. , vol. 5, no. 4, pp. 796–800, Oct. 2008.
[13] I. W. Selesnick, R. G. Baraniuk, and N. G. Kingsbur, "The dual-treecomplex wavelet transform," IEEE Signal Prcess. Mag. , vol. 22, no. 6,pp. 123–151, Nov. 2005.
[14] J. L. Starck, F. Murtagh, and J. M. Fadili, Sparse Image and Signal Processing: Wavelets, Curvelets, Morphological Diversity. Cambridge, U.K.: Cambridge Univ. Press, 2010.
[15] A. Buades, B. Coll, and J. M. Morel, "A review of image denoising algorithms, with a new one," Multisc. Model. Simul. vol. 4, no. 2, pp. 490–530, 2005.
[16] A. Buades, B. Coll, and J. M. Morel, "Denoising image sequences doesnot require motion estimation," in Proc. IEEE Conf.Audio, Video Signal Based Surv. , 2005, pp. 70–74.
[17] M. Protter, M. Elad, H. Takeda, and P. Milanfar, "Generalizing the nonlocal-means to super-resolution reconstruction,"IEEE Trans. Image Process., vol. 18, no. 1, pp. 36–51, Jan. 2009.
[18] Z. Wang and A. C. Bovik, "A universal image quality index," IEEE Signal Process. Lett., vol. 9, no. 3, pp. 81–84, Mar. 2002.

[19] Z. Wang and A. C. Bovik. A universal image quality index. IEEE Signal Processing Letters, 9(3):81–84, 2002.

