A Novel Algorithm for Satellite Image Resolution Enhancement Using Wavelet-Domain Approach Based On (DT-CWT) and Non Local Means (NLM)

Manjoor.Syed, S Naga Kishore Bhavanam

***Abstract*— In this paper, Resolution enhancement (RE) model has one of the biggest disadvantage (drawback) is losing high frequency contents (which results in blurring). Discrete wavelet transform based (DWT) RE scheme generates artifacts due to a DWT shift-variant property. For RE of the satellite images, here, new wavelet domain approach based on dual-tree complex wavelet transform (DT-CWT) and nonlocal means (NLM) is proposed. A satellite input image is decomposed by DT-CWT which is nearly shift invariant to obtain high-frequency sub bands. To interpolate the high-frequency sub bands and the low-resolution (LR) input images; in this paper the Lanczos interpolator is used. The high frequency sub bands are passed through an NLM filter to cater for the artifacts generated by DT-CWT. To obtain a resolution-enhanced image we are combining the filtered high-frequency sub bands and the LR input image by using inverse DT-CWT. Objective and subjective analyses show superiority of the new proposed technique over the conventional and state-of-the-art RE techniques.**

***Index Terms*— DT-CWT, RE, DWT, NLM, LR, NLM.**

I. INTRODUCTION

Resolution (spatial, spectral, and temporal) is the limiting factor for the utilization of remote sensing data (satellite imaging, etc.). In digital image processing , satellite images are categorized to less sensitive images (unprocessed).In satellite images spatial resolution is associated (a high spatial resolution is associated with a low spectral resolution and vice versa) low spectral resolution and vice versa.[1]. So, spectral, as well as spatial, resolution enhancement (RE) is desirable. Interpolation has been widely used for RE [2], [3].

Basically interpolation techniques based on nearest neighbors, for example, include nearest neighbor, bilinear, bicubic, and Lanczos. The Lanczos interpolation (windowed form of a sinc filter) is superior to its counterparts (including nearest neighbor, bilinear, and bicubic) because it has increased ability to detect edges and linear features. And it also offers the best compromise in terms of reduction of aliasing, sharpness, and ringing [4]. Methods based on vector-valued image regularization with partial differential equations (VVIR-PDE) [5] and inpainting and zooming using sparse representations [6] are now state of the art in the field (mostly applied for image inpainting but can be also seen as interpolation). RE schemes (which are not based on wavelets) suffer from one major drawback of losing high frequency contents (which results in blurring). RE by using wavelet domain is a new research area, and recently, many algorithms [discrete wavelet transform (DWT) [7], stationary wavelet transform (SWT) [8], and dual-tree complex wavelet transform (DT-CWT) [9] have been proposed [7]–[11]. An RE scheme was proposed in [9] using DT-CWT and bicubic interpolations, and results were compared (shown superior) with the conventional schemes (i.e., nearest neighbor, bilinear, and bicubic interpolations and wavelet zero padding). More recently, in [7], a scheme based on DWT and bicubic interpolation was proposed, and results were compared with the conventional schemes and the state-of-art schemes (wavelet zero padding and cyclic spinning [12] and DT-CWT [9]). But, DWT is shift variant, which causes artifacts in the RE image, and has a lack of directionality; so, DT-CWT is almost shift and rotation invariant [13]. DWT-based RE schemes generate artifacts (due to DWT shift-variant property). In this paper, a DT-CWT-based nonlocal-means-based RE (DT-CWT-NLM-RE) technique is proposed, using the DT-CWT, Lanczos interpolation, and NLM. This DT-CWT technique is nearly shift invariant and directional selective. Moreover, DT-CWT preserved the usual properties of perfect reconstruction with well-balanced frequency responses [13], [14]. Consequentially, DT-CWT gives better results after the modification of the wavelet coefficients and provides less artifacts, as compared with traditional DWT. Since the Lanczos filter offer less aliasing, sharpness, and minimal ringing, so, this one is the better choice for RE. NLM filtering [15] is used to further enhance the performance of DT-CWT-NLM-RE by reducing the artifacts. The results (for spatial RE of optical images) are compared with the best performing techniques [5], [7], [9].

II. PRELIMINARIES

A. *NLM Filtering*

The NLM filter is an extension of neighborhood filtering algorithms. Which is based on the assumption i.e., that image content is likely to repeat itself within some neighborhood (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 $Y(p,q)$ (within frame and in the neighboring frames) [16]. This feature provides a way to

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estimate the pixel value from noise contaminated images. In a 3-D NLM algorithm, the estimate of a pixel at position (p, q) is

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

Here, m is the frame index, and N represents the neighborhood of the pixel at location (p, q). K values are the filter weights, i.e.

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

Here, 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(.) is a geometric distance function. K is inversely proportional to the distance between Y (p, q) and Y (r, s).

B. *NLM-RE*

RE is achieved by modifying NLM with the following model [17]:

$$L_m = IJQX + n \qquad (3)$$

From equation (3) L_m is the vectorized low-resolution (LR) frame, I is the decimation operator, J is the blurring matrix, Q is the warping matrix, X is the vectorized high-resolution (HR) image, and denotes the Gaussian white noise. The main objective is to restore X from a series of L. Penalty function ∈ is defined as

$$\in^2 = \frac{1}{2}\sum_{m=1}^{M} \|IJQx - Y_m\|_2^2 + \lambda R(x) \qquad (4)$$

Here, from, equation (4) R is a regularization term, λ is the scale coefficient, x is the targeted image, and Y_m is the LR input image. In [17], the total variation kernel is chosen to replace R, acting as an image deblurring kernel. To simplify the algorithm, a separation of the problem in (4) is done by minimizing

$$\in_{fusion}^2 (Z) = \frac{1}{2}\sum_{m=1}^{M} (IQZ - L_m)^T o_m (IQZ - L_m) \qquad (5)$$

Here, Z is the blurred version of the targeted image, and O_m is the weight matrix, followed by minimizing a deblurring equation [11], i.e.,

$$\in_{RE}^2 (X) = \|JX - Z\|_2^2 + \lambda R(Z) \qquad (6)$$

Pixel wise solution of (5) can be obtained as

$$\hat{z} = \frac{\sum_{m=1}^{M} \sum_{(r,s)\in N(p,q)} Y_m^r(r,s) K_m^r(r,s)}{\sum_{m=1}^{M} \sum_{(r,s)\in N(p,q)} K_m^r(r,s)} \qquad (7)$$

Here, the superscript r refers to the HR coordinate.

Instead of estimating the target pixel position in nearby frames, this algorithm considers all possible positions where the pixel may appear; therefore, motion estimation is avoided [11]. Equation (7) apparently resembles (1), but (7) has some differences as compared with (1). The weight estimation in (2) should be modified because 'K' is corresponding matrix O has to be of the same size as the HR image. Therefore, a simple up scaling process to patch V is needed before computing K. The total number of pixel Y in (7) should be equal to the number of weights K. Thus, a zero-padding interpolation is applied to L before fusing the images [11].

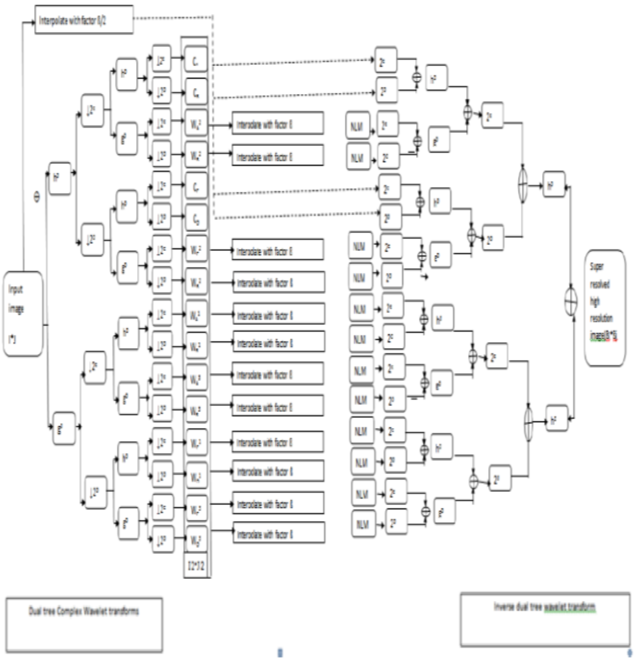

Figure 1: Block diagram of the proposed DT-CWT-RE algorithm.

III. PROPOSED ALGORITHM

In this paper, proposed algorithm DT-CWT-NLM-RE. By using DT-CWT we decompose the LR input image (for the multichannel case, each channel is separately treated) in different sub bands (i.e., C_i and W_j^i , where $i \in \{A, B, C, D\}$ and $j \in \{1,2,3\}$), as shown in Fig. 1. C_i values are the image coefficient sub ands, and w_i^j are the wavelet coefficient sub bands. Here the subscripts A, B, C, and D represent the coefficients at the even-row and even-column index, the odd-row and even column index, the even-row and odd-column index and the odd-row and odd-column index, respectively, where as h and g represent the low-pass and high-pass filters, respectively. And the superscript e and o represent the even and odd indices, respectively. W_i^j Values are interpolated by factor β using the Lanczos interpolation (having good approximation capabilities) and Combined with the β/2-interpolated LR input image. Since C_i contains low-pass-filtered image of the LR input image, therefore, high-frequency information is lost. To cater for it, we have used the LR input image instead of C_i . Although the DT-CWT is almost shift invariant [14], therefore, it may produce artifacts after the interpolation of W_i^j so interpolated W_i^j values are passed through the NLM filter. After that we apply the inverse DT-CWT to these filtered to remove these artifacts, NLM filtering is used.

All subbands along with the interpolated LR input image to reconstruct the HR image. The results presented show that the proposed DT-CWT-NLM-RE algorithm gives better than the existing wavelet-domain RE algorithms in terms of the peak-signal to noise ratio (PSNR), the MSE, and the Q-index [18].

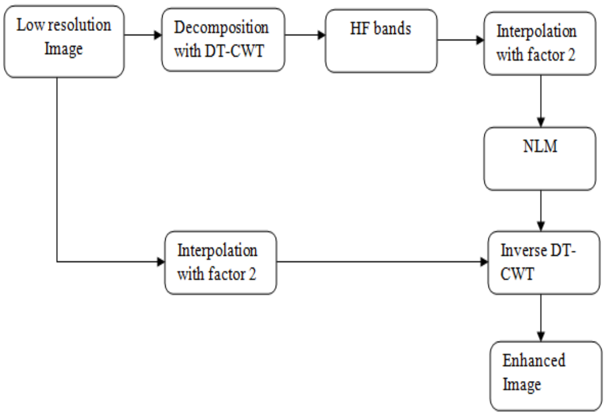

Figure 2: Proposed Block diagram

V. SIMULATION RESULTS

The input image is the low resolution image having a resolution of [128*128] which is processed using the proposed algorithm and the output is the high resolution image with resolution [256*256].

Figure 1: Intput Image
(courtesy from Acharya Nagarjuna University)

Figure 2 : Output Image (High Resolution Image)
(courtesy from Acharya Nagarjuna University)

VI. CONCLUSION

In this paper, an RE technique based on DT-CWT and an NLM filter has been proposed. By using DT-CWT technique decomposes the LR input image. Lanczos interpolator is used to interpolate for Wavelet coefficients and the LR input image. DT-CWT is nearly shift invariant and generates less artifacts when compared with DWT. NLM filtering is used to overcome the artifacts generated by DT-CWT and to further enhance the performance of the proposed technique in terms of MSE, PSNR, and Q-index. Simulation results show the superior performance of proposed techniques.

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