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Performance Analysis of Image Enhancement Using Dual-Tree Complex Wavelet Transform and Nonlocal Means

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Abstract:- Resolution enhancement (RE) schemes which are not based on wavelets has one of the major drawbacks of losing high frequency contents which results in blurring. The discrete wavelet- transform-based (DWT) Resolution Enhancement scheme generates artifacts (due to a DWT shift-variant property). A wavelet-Domain approach based on dual-tree complex wavelet transform (DT-CWT) & nonlocal means (NLM) is proposed for RE of the satellite images. A satellite input image is decomposed by DT-CWT (which is nearly shift invariant) to obtain high-frequency sub bands. Here the Lanczos interpolator is used to interpolate the high-frequency sub bands & the low-resolution (LR) input image. The high frequency sub bands are passed through an NLM filter to cater for the artifacts generated by DT-CWT (despite of it's nearly shift invariance). The filtered high-frequency sub bands and the LR input image are combined by using inverse DTCWT to obtain a resolution-enhanced image. Objective and subjective analyses show superiority of the new proposed technique over the conventional and state-of-the-art RE techniques.

Keywords:- Dual-Tree Complex Wavelet Transform (DT-CWT), Lanczos Interpolation, Resolution Enhancement (RE), shift variant.

I. INTRODUCTION

Resolution (spatial, spectral, and temporal) is the limiting factor for the utilization of remote sensing data by satellite imaging, etc. In satellite image Spatial and spectral resolutions are related (a high spatial resolution is associated with a low spectral resolution and vice versa) with each other [1]. So, spectral, as well as spatial, resolution enhancement (RE) is most by desirable. Interpolation has been widely used for RE [2], [3]. Commonly used interpolation techniques are based on nearest neighbours include nearest neighbour, bilinear, bi-cubic, and Lanczos. The Lanczos interpolation (windowed form of a sinc filter) is superior to its counterparts (including nearest neighbour, bilinear, and bi-cubic) 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]. The Methods based on vector-valued image regularization with partial differential equations (VVIRPDE) [5] and in painting and zooming using sparse representations [6] are now state of the art in the field (i.e,mostly applied for image in painting 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 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 by 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) [9], More recently in [7], a scheme based on DWT and bicubic interpolation was proposed, and results were compared with the conventional schemes and the stateof- art schemes (wavelet zero padding and cyclic spinning [12] and DT-CWT [9]). But, DWT is shift variant, which causes the 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 DTCWT- based nonlocal-means-based RE (DT-CWT-NLMRE) 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 fewer 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. LITERATURE REVIEW

Existing method:

- Discrete Wavelet Transform
- Stationary Wavelet Transform
- Nearest neighbour based pixel insertion

Proposed method:

Resolution enhancement of low resolution satellite image base on,

- Dual Tree CWT multi scale decomposition
- Neighbourhood insertion with interpolation technique
- Edge Preserving filter- Non local means

III. PERFORMANCE ANALYSIS OF ALGORITHMS

A. NLM Filtering

The NLM filter (an extension of neighborhood filtering algorithms) is based on the assumption that image content is likely to repeat itself within some neighborhood (in the image) [15] and in neighboring frames [16]. It computes denoised pixel by the weighted sum of the surrounding pixels of (within frame and in the neighboring frames) [16]. This feature provides a way to estimate the pixel value from noisecontaminated images. In a 3-D NLM algorithm, the estimate position i.e, of a pixel is

$$X(p,q) = \frac{\sum_{m=1}^{M} \sum_{(r,s)\in N(p,q)} Ym(r,s)Km(r,s)}{\sum_{m=1}^{M} \sum_{(r,s)\in N(p,q)} Km(r,s)} \qquad (1)$$

Where 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.

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

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

B. NLM-RE

Resolution Enhancement is achieved by modifying NLM with the following model proposed in [17]:

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

Where indicates 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) im image, and n denotes the Gaussian white noise. The aim is to restore X from a series of L.

Penalty function is defined as

$$\epsilon^2 = ½\sum_{m=1}^{M} \|IJQx - Ym\|_2^2 + \lambda R(x) \qquad (4)$$

$$\epsilon_{fusion}^2 = ½\sum_{m=1}^{M} (IQZ - L_m)^T o_m (IQZ - L_m) \qquad (5)$$

Where M is a regularization term, λ is the scale coefficient, x is the targeted image, and is the LR input image. The total variation kernel is chosen to replace R, acting as an image deblurring kernel by [17]. To simplify the algorithm, a separation of the problem in (4) is done by minimizing Where Z is the blurred version of the targeted image, and is the weight matrix, followed by minimizing a deblurring equation [11], i.e.,

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

Pixel wise solution of (5) can be obtained as

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

Where the superscript r refers to the HR coordinate. Instead of estimating the target pixel position in nearby frames, this algorithm considers that 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 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 the 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].

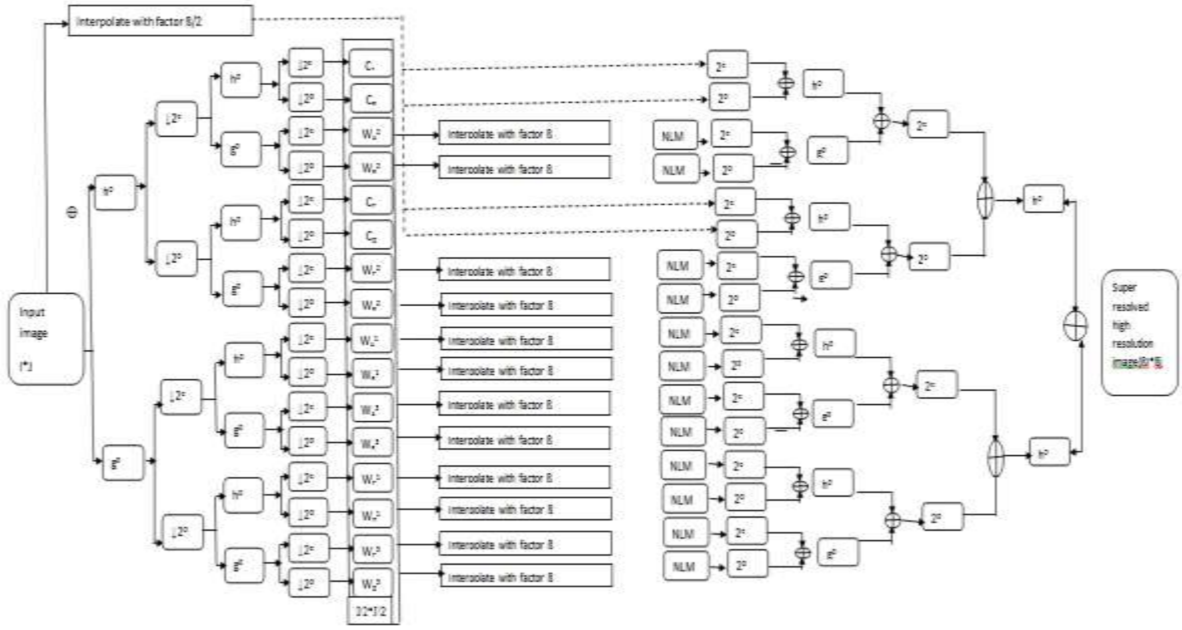

Fig. 1 DUAL TREE Block Diagram

IV. PROPOSED WORK

In the proposed Work model we decompose the LR input image in different sub bands by using DT-CWT.The simulated Values are interpolated by factor β(beta) using the Lanczos interpolation and Combined with the β/2- interpolated LR input image, to remove artifacts, NLM filtering is used. All interpolated values are passed through the proposed filter. After that we apply the inverse DT-CWT to these filtered sub bands along with the interpolated LR input image to reconstruct the HR image.

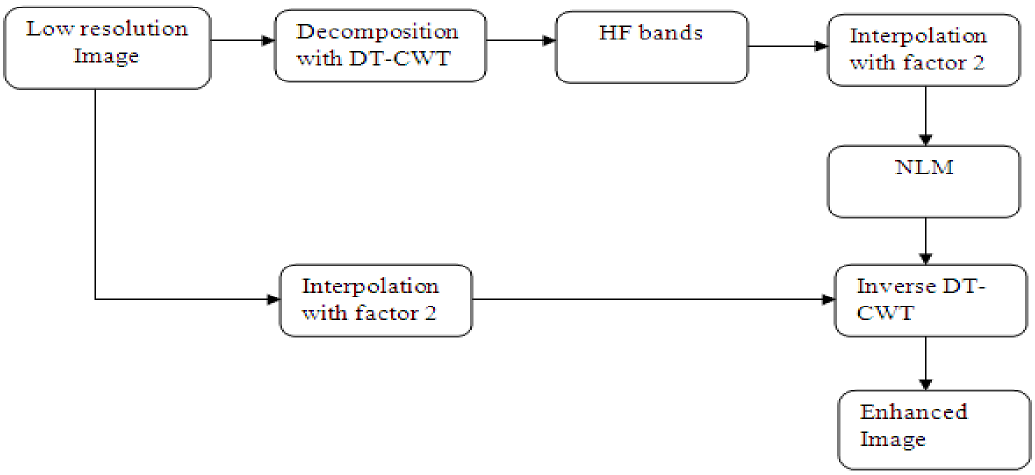

Fig. 2 Proposed Block Diagram

V. SIMULATION RESULT& CONCLUSION

Fig.3 Original Image

Fig.4 Transformed Image

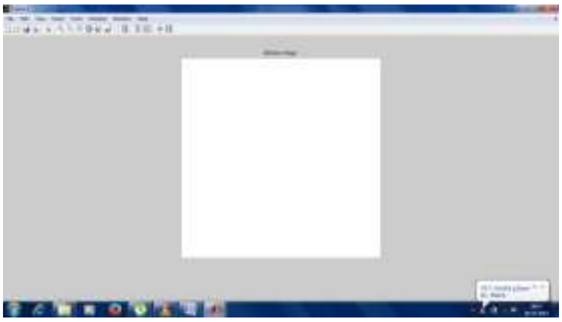

Fig.5 Biterror Image

TABLE I comparison of the existing and proposed techniques for the "cameraman.tif" image

Algorithm	MSE	PSNR(Db)	Q-index
Lanczos	0.0253	15.9770	0.9614
DT-CWT-RE	0.0242	16.1576	0.9986
Proposed DT-CWT-RE	0.0215	16.6658	0.9986
Proposed DT-NML-CWT-RE	0.0174	17.5895	0.9999

In this paper an RE technique based on DT-CWT and an NLM filter has been proposed. This technique decomposes the LR input image using DT-CWT. By using the Lanczos interpolator Wavelet coefficients and the LR input image was interpolated. This DT-CWT is nearly shift invariant and generates fewer artifacts as compared with DWT. NLM filtering is used to overcome the artifacts generated by the DT-CWT and to further enhance the performance of the proposed technique in terms of MSE, PSNR, and Qindex. Experimental results show the superior performance of proposed techniques. DT-CWT-NLM-RE are much better than the RE images obtained using other techniques. Table I shows that the proposed techniques provide improved results in terms of MSE, PSNR, and *Q*-index [18], as compared with other techniques. It is clear that the proposed DT-CWT-RE and DTCWT- NLM-RE schemes techniques qualitatively and quantitatively.

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